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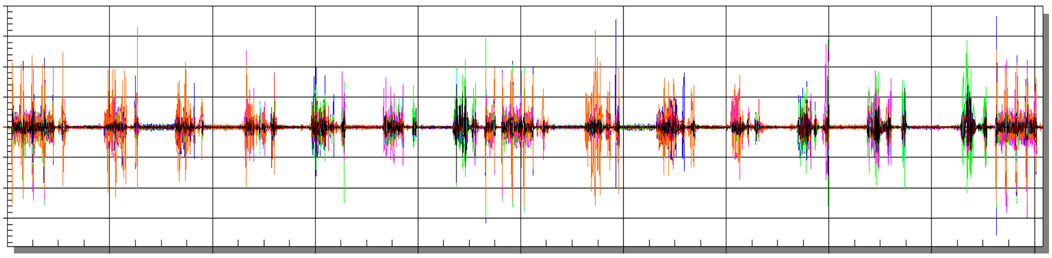
PERTH, WESTERN AUSTRALIA 6845

SENSOR PLACEMENT, OPERATION IDENTIFICATION, AND FAULT DETECTION FOR AUTOMATED CONSTRUCTION MONITORING



A Thesis

Submitted by

APARNA HARICHANDRAN

For the award of the degree

Of

DOCTOR OF PHILOSOPHY

January, 2022

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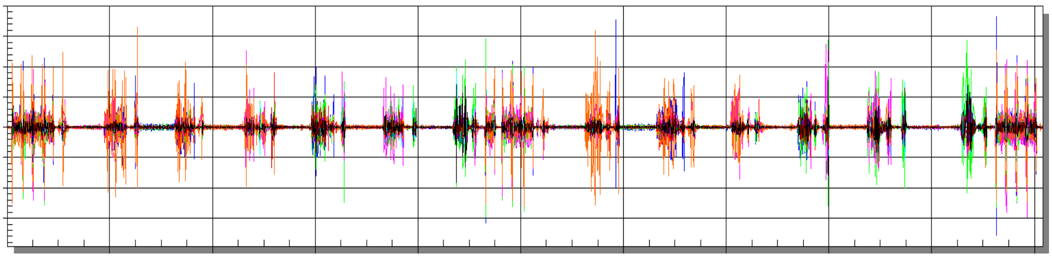

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THESIS CERTIFICATE

This is to undertake that the Thesis titled, **SENSOR PLACEMENT, OPERATION IDENTIFICATION, AND FAULT DETECTION FOR AUTOMATED CONSTRUCTION MONITORING** submitted by me to the Indian Institute of Technology Madras, for the award of Ph.D. (Joint Doctoral Degree with Curtin University, Perth, Australia) is a bona fide record of the research work done by me under the supervision of Prof. Benny Raphael and Prof. Abhijit Mukherjee. The contents of this Thesis, in full or in parts, have not been submitted to any other Institute or University for the award of any degree or diploma.

Chennai 600 036	**Research Scholar**
Date: 20/01/2022	Aparna Harichandran

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Indian Institute of Technology Madras,	Engineering, Curtin University,
Chennai, India	Perth, Australia

For the everlasting memory of my dear father K V Harichandran and his unfinished dreams…

List of Publications

I REFERRED JOURNALS BASED ON THE THESIS

1. **Aparna Harichandran**, Benny Raphael and Abhijit Mukherjee. A Hierarchical Machine Learning Framework for the Identification of Automated Construction Operations. Journal of Information Technology in Construction. 26, 591–623 (2021). DOI: 10.36680/j.itcon.2021.031
2. **Aparna Harichandran**, Benny Raphael and Abhijit Mukherjee. Development of Automated Top-Down Construction System for Low-rise Building Structures. International Journal of Industrialized Construction. 1, 22–33 (2020). DOI: doi.org/10.29173/ijic217.
3. **Aparna Harichandran**, Benny Raphael and Abhijit Mukherjee. Activity Recognition and Early Fault Detection in Automated Construction through a Machine Learning Framework. Computer-Aided Civil and Infrastructure Engineering (under review).

II REFERRED JOURNALS (Others)

1. Benny Raphael and **Aparna Harichandran**. Sensor Data Interpretation in Bridge Monitoring - A Case Study. Frontiers in Built Environment. 5, 148 (2020). DOI: doi.org/10.3389/fbuil.2019.00148.

III PRESENTATIONS IN CONFERENCES

1. **Aparna Harichandran**, Benny Raphael and Abhijit Mukherjee. A Robust Framework for Identifying Automated Construction Operations. 37th International Symposium on Automation and Robotics in Construction, Japan, October, 2020.
2. **Aparna Harichandran**, Benny Raphael and Abhijit Mukherjee. Determination of Automated Construction Operations from Sensor Data using Machine Learning. 4th International Conference on Civil & Building Engineering Informatics, Japan, November, 2019. (**Best Presentation Award**)
3. **Aparna Harichandran**, Benny Raphael and Abhijit Mukherjee. Automated Top-down Construction. Smart Materials, Smart Construction, Smart Structures Workshop, Australia, November, 2019.

4. **Aparna Harichandran**, Benny Raphael and Abhijit Mukherjee. Identification of the Structural State in Automated Modular Construction. 36th International Symposium on Automation and Robotics in Construction, Canada, May, 2019.
5. **Aparna Harichandran**, Benny Raphael and Koshy Varghese. Inferring Construction Activities from Structural Responses using Support Vector Machines. 35th International Symposium on Automation and Robotics in Construction, Germany, July, 2018.

IV PUBLICATIONS IN CONFERENCE PROCEEDINGS

1. **Aparna Harichandran**, Benny Raphael and Abhijit Mukherjee. A Robust Framework for Identifying Automated Construction Operations. Proceedings of 37th International Symposium on Automation and Robotics in Construction, Japan, 473-480 (2020). DOI: doi.org/10.22260/ISARC2020/0066.
2. **Aparna Harichandran**, Benny Raphael and Abhijit Mukherjee. Determination of Automated Construction Operations from Sensor Data using Machine Learning. Proceedings of 4th International Conference on Civil & Building Engineering Informatics, Japan, 77–84 (2019). ISBN978-4-600-00276-3.
3. **Aparna Harichandran**, Benny Raphael and Abhijit Mukherjee. Automated Top-down Construction. Proceedings of Smart Materials, Smart Construction, Smart Structures Workshop, Australia, 15 (2019). ISBN:978-0-6487425-0-0.
4. **Aparna Harichandran**, Benny Raphael and Abhijit Mukherjee. Identification of the Structural State in Automated Modular Construction. Proceedings of 36th International Symposium on Automation and Robotics in Construction, Canada, 187–193 (2019). DOI: doi.org/10.22260/ISARC2019/0026.
5. **Aparna Harichandran**, Benny Raphael and Koshy Varghese. Inferring Construction Activities from Structural Responses using Support Vector Machines. Proceedings of 35th International Symposium on Automation and Robotics in Construction, Germany, 332–339 (2018). DOI: doi.org/10.22260/ISARC2018/0047.

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Finally, my incredible PhD journey is coming to an end. The past few years have been undoubtedly the most arduous and fulfilling period in my life. I have met numerous beautiful minds who have challenged my intellect, remoulded my perspective and encouraged my pursuit. I would like to extend my sincere gratitude to all those people for their unconditional love and support throughout this period.

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Hapkido club; Ambili, Haripriya, Mayuri, and Dr. Gitakrishnan Ramadurai from the IITM Art of Living Club; all members of the Curtin Karate club and friends in the BTCM division were an integral part of this journey. I have learned a lot from you and am forever grateful for our memories together.

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Aparna Harichandran

ABSTRACT

Automation alleviates some of the safety concerns in conventional construction enhances several aspects of existing practices. However, it presents intricate scenarios involving the machines and the workers requiring an efficient monitoring system for safe implementation. The crucial steps in construction monitoring are activity recognition and fault detection. Existing studies on construction equipment monitoring have focused mainly on activity recognition and tracking; fault detection has been seldom explored.

The overall aim of this research is to develop a robust monitoring system for automated construction. The methodology adopted for the current research is quantitative theory building based on case studies. This research methodology involves the development of a conceptual framework followed by empirical verification and iterative modifications. This study proposes a novel activity recognition and fault detection framework called HUS-ML (Hybrid Unsupervised and Supervised Machine Learning). The critical conceptual components of the framework comprises a sensor placement strategy, an operation identification methodology, and a fault detection method. The implementation of this monitoring framework starts with the measurement system design using the preliminary measurements during automated construction. The configuration of the measurement system is determined through the sensor placement methodology proposed in this study. Then the responses from the structure during the Automated Construction System (ACS) operations are measured and supplied to the HUS-ML framework. A hierarchical arrangement of the identification problems in this framework extracts the high-level operation details. Supervised learning and unsupervised learning ensure accurate identification of normal operations and faulty

condition. First, identification is attempted through supervised learning using training data of previous operations. Then an anomaly detection algorithm is applied to spot any unseen faulty conditions. If the identified operation is normal, the progress of construction is updated in the database. If the operation is identified as faulty during supervised learning (known faulty operations), corrective actions can be taken after completing hierarchical identification. If the faulty conditions are detected through unsupervised learning (unforeseen faulty operations), further investigation is needed before corrective actions.

The proposed framework has been validated on an automated construction system that was custom designed and fabricated as part of this research. This system has been developed for low rise building construction that follows an automated top-down construction method. Acceleration measurements from the structure were used for identifying operations and faulty conditions. The experiments were conducted in a controlled laboratory condition under the supervision of trained experts. It involves normal operation cycles and potential faulty conditions in the automated construction. The HUS-ML framework and its components were independently validated. The performance of the proposed framework was benchmarked by comparing it with conventional approaches. The algorithms for operation recognition and fault detection were iteratively modified to obtain the desired performance. In addition to conventional machine learning algorithms, advanced deep learning classifiers such as LSTM (Long Short-Term Memory) networks and various data augmentation methods were explored for identifying automated construction activities. The generalizability of the proposed framework was assessed through its application on a benchmark dataset. The HUS-ML framework shows promising results in identifying normal automated construction operations. The framework also detects early signs of failure, even with limited data. It outperforms the conventional approach in activity recognition and fault detection. The proposed framework demonstrates its potential for developing a robust monitoring system.

KEYWORDS: Construction Monitoring, Machine Learning, Automated Construction, Sensor Placement, Activity Recognition, and Fault Detection.

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ABBREVIATIONS

ABCS	Automated structural steel Building Construction System
ACS	Automated Construction System
AI	Artificial Intelligence
AM	Accelerometer
AMURAD	Automatic Up-Rising Construction by Advanced Technique
ANN	Artificial Neural Network
BPNN	Back Propagation Neural Network
CBC	Crew-balance Charts
CML	Conventional Machine Learning
Cn	Column n
CNN	Convolutional Neural Network
CS	Construction Stage
DA	Discriminant Analysis
DT	Decision Tree
DTW	Dynamic Time Warping
DL	Deep Learning
ELM	Extreme Learning Machine
Faster R-CNN	Faster Region-proposal Convolutional Neural Network
FSn	Feature Selection method n
FTA	Fault Tree Analysis
GMM	Gaussian Mixture Model
HMM	Hidden Markov Model
HOG	Histogram of Oriented Gradients

HPC	High-Performance Computing
HUS-ML	Hybrid Unsupervised and Supervised Machine Learning
HVAC&R	Heating, Ventilation, Air Conditioning, and Refrigeration
ICT	Information and Communication Technology
IM	Induction motor
IMU	Inertial Measurement Unit
IQR	Interquartile range
kNN	k-Nearest Neighbour
LR	Linear Regression
LSTM	Long Short-Term Memory networks
MFCC	Mel-Frequency Cepstral Coefficients
ML	Machine Learning
NB	Naïve Bayes
NCR	Non-Conformance Report
RCACS	Robotic and Crane based Automatic Construction System
RMS	Root Mean Square
RNN	Recurrent Neural Networks
ROD	Robot-Oriented Design
RTMMS	Real-Time Monitoring and Management System
SD	Standard deviation
Sn	Support n
SOP	Safe/Standard Operating Procedures
SVM	Support Vector Machines
SMART	Shimizu Manufacturing System by Advanced Robot Technology
SMO	Sequential Minimum Optimization

STFT	Short-Time Fourier Transform
TDL	Tracking-Learning-Detection

NOTATION

English Symbols

b	bias
c_t	Cell state at timestep t
d	Feature
$d_{cv}^{(i)}$	i^{th} datapoint in the cross-validation dataset
f	Forget gate
g	Cell candidate
h_t	Hidden state at timestep t
E	Entropy
i	Input gate
l	Label of an instance
$l_{cv}^{(i)}$	Label for the i^{th} datapoint in the cross-validation dataset
m	Number of training instances
m_{cv}	Number of instances in the cross-validation dataset
o	Output gate
p	Gaussian probability distribution
T	Threshold for probability
R	Recurrent weight
S	Maximum number of intervals at a sensor location
v	Variable for sensor placement
W	Input weight
x_t	Value of the time series data at timestep t

Greek Symbols

μ	Mean
σ	Standard deviation
σ_c	State activation function
σ_g	Gate activation function

CHAPTER 1

INTRODUCTION

1.1 RESEARCH MOTIVATION

Growing demand for complex and quality infrastructure, improved working conditions, high productivity, and economy make automation and robotics in construction imperative (Castro-Lacouture, 2009; Harichandran *et al.*, 2021). Besides, workplace accidents and fatalities in the construction industry are alarmingly high (Bureau of Labor Statistics, 2018, 2020). Automating construction activities can alleviate most of the safety incidents in conventional construction. Researchers have studied automation of various aspects of construction such as planning and scheduling (Kim *et al.*, 2013; Sheikhkhoshkar *et al.*, 2019; Wang and Azar, 2019), construction materials and methods (Tamayo *et al.*, 2018; Lemke *et al.*, 2019; Men and Zhang, 2019), construction progress monitoring (Golparvar-Fard *et al.*, 2009; Harichandran *et al.*, 2018; Mahami *et al.*, 2019), resource allocation and tracking (Azar, 2016; Kargul *et al.*, 2017; Hongjo Kim *et al.*, 2018), quality assurance and quality control (Zhong *et al.*, 2018; Kazemian *et al.*, 2019; Lakhal *et al.*, 2019), improving safety at the worksite (Park *et al.*, 2017; Wang *et al.*, 2017; Yang and Ahn, 2019), assessing labour productivity (Joshua and Varghese, 2014; Akhavian and Behzadan, 2016; Cheng *et al.*, 2017), and structural health monitoring (Alavi *et al.*, 2016; Liu and Zhang, 2019; Valero *et al.*, 2019). However, the application of automation and robotic technologies in actual construction sites is still at the early stages. In particular, automated systems for the construction of low-rise buildings are limited. A vast majority of Automated Construction Systems (ACS) and related technologies were developed for high rise buildings (Hamada *et al.*, 1998; Gassel, 2005; Bock and Linner, 2016b). System Skanska, J-up and NCC

Komplett are the three low-rise Automated Construction Systems (ACS) out of thirty ACS available in published literature (Bock and Linner, 2016b). None of these low-rise ACS has implemented an integrated automated monitoring system for ensuring construction safety.

Urgent relocation, treatment or temporary accommodation of a large population affected by natural calamities or pandemics are examples of situations that demand rapid construction of low-rise buildings. In this context, automation and robotic technologies for low-rise buildings are gaining increasing attention. Raphael *et al.* proposed a top-down construction method for low-rise buildings with automated coordinated lifting (Raphael *et al.*, 2016). This method is further developed into an automated top-down construction system for modular construction of low-rise buildings (Harichandran *et al.*, 2019b, 2019a, 2020b, 2021).

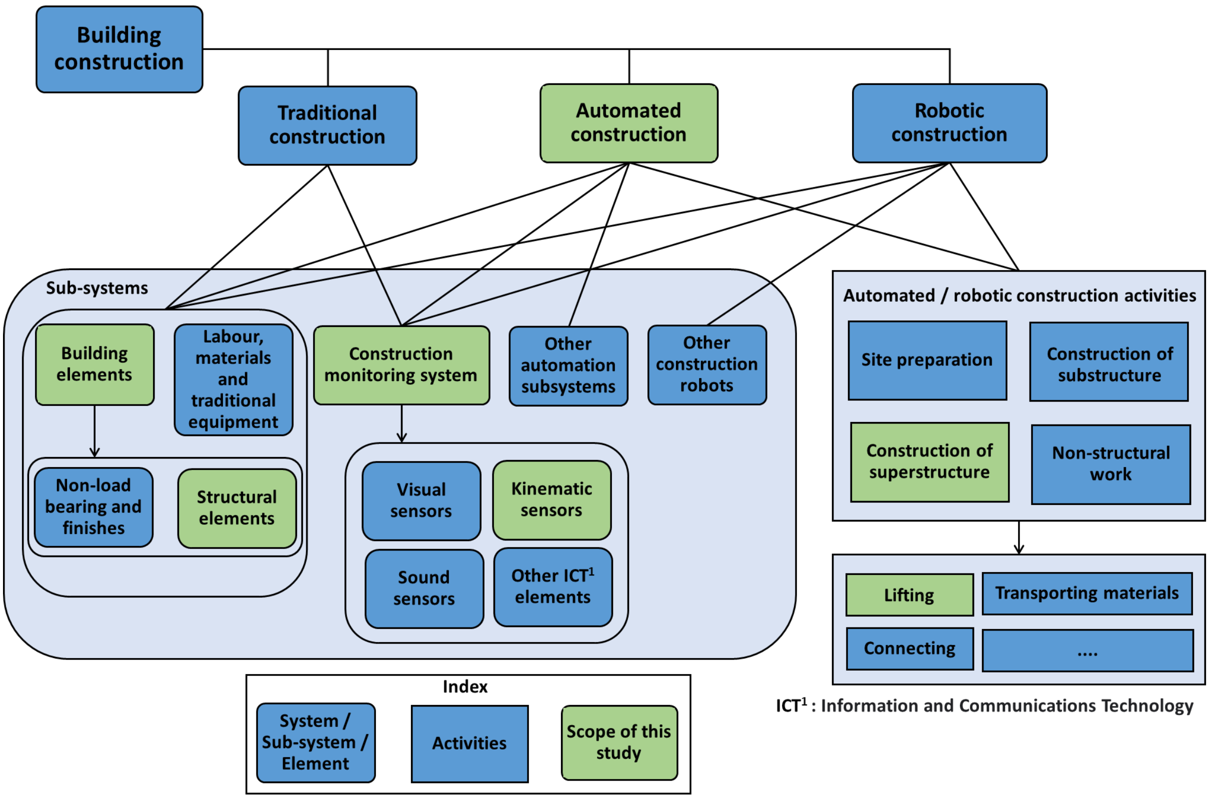


Figure 1.1 Role of the current study on the context of automated/robotic construction

Even amidst rapid technological advancements, the construction industry is far from a fully automated or robotic construction site (Melenbrink *et al.*, 2020). Until we reach this stage, automation systems, robots and workers need to coexist on construction sites (Bock and Linner, 2016a). These scenarios involve complex interactions between machines and workers and have risks associated with unsafe conditions. This necessitates the development of an automated monitoring system for safe operations (Figure 1.1). The challenges in this context lead to the following research questions and objectives.

- How to monitor automated construction operations for ensuring safety?
- How to systematically collect useful data from the structure under automated construction?
- How to make sense of data from the monitoring system to make decisions about the construction process?

1.2 OBJECTIVES AND SCOPE

1.2.1 Research objectives

The overall goal of this research is to develop a robust monitoring system for automated construction. This requires accurately identifying construction activities and associated faulty conditions. The specific objectives addressed in this research are the following.

1. Develop an automated operation recognition and fault detection framework which takes into account specific requirements of the automated construction domain, such as:

    1.1. High accuracy of identification

    1.2. High level of details of activities

    1.3. Ability to detect early signs of failure with limited data

2. Design algorithms and methodologies for the efficient implementation of the framework. This includes algorithms for:

    2.1. Sensor placement

    2.2. Operation identification

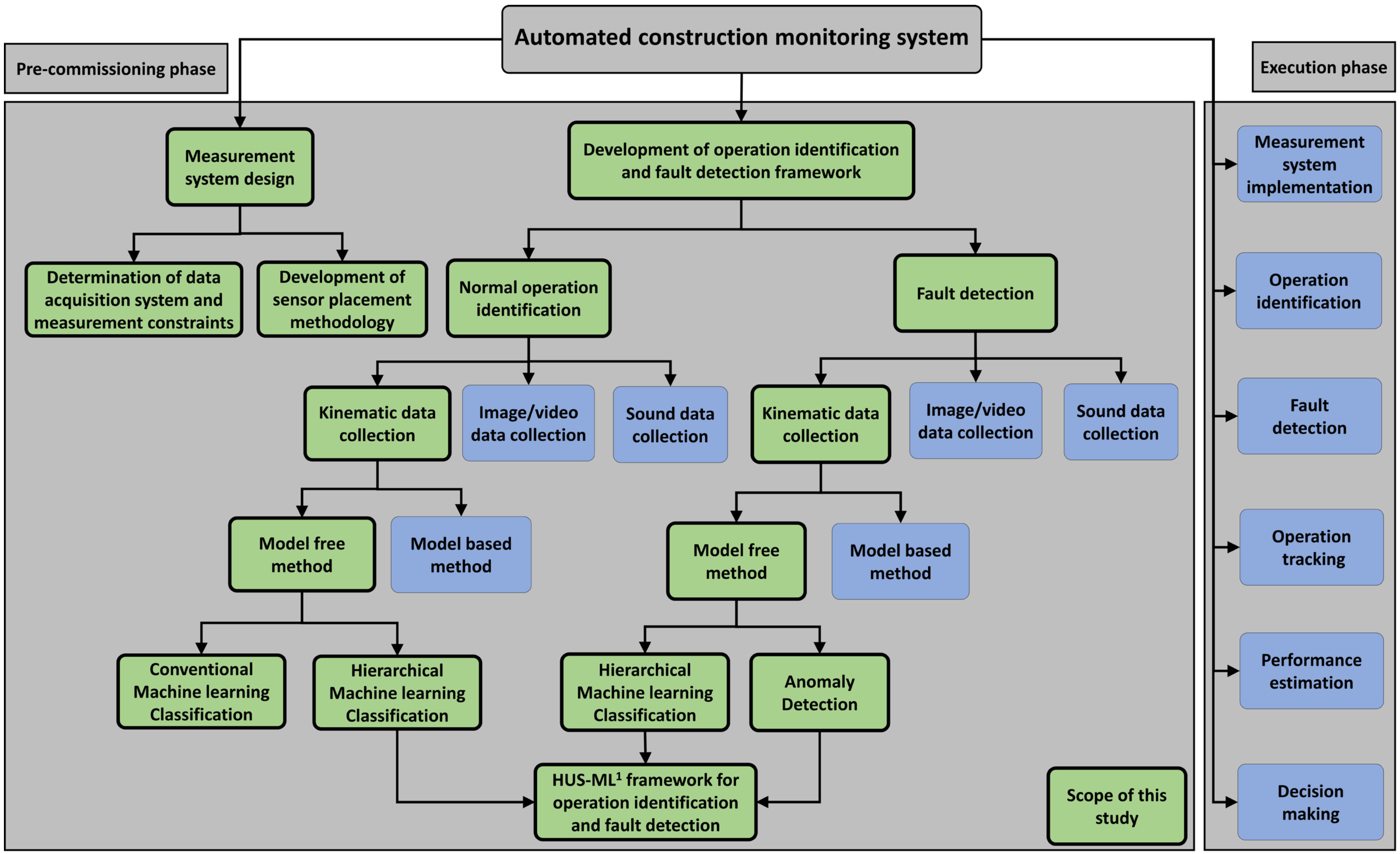
    2.3. Fault detection

3. Design the experimental setup and evaluate the feasibility of the application of the framework on a full-scale automated construction system.

1.2.2 Scope of the research

The broader context of the current study is illustrated in Figure 1.2, and the scope is highlighted in green. An automated construction monitoring system consists of several components such as measurement, operation identification, and fault detection. The framework and algorithms for construction monitoring are developed in the pre-commissioning phase and implemented in actual construction sites in the execution phase. The methodologies developed in this study are evaluated in a controlled laboratory environment.

The scope of the study is automatically identifying the operations and detecting the faulty conditions during the construction of a low-rise structural frame through an Automated Construction System (ACS). Automation is involved in two parts of the study: 1) operation identification and fault detection through intelligent algorithms, 2) construction method. The first part of the study contributes to the vast body of literature in the domain of construction informatics, especially in the area of construction equipment monitoring. Inferences pertaining to the second part of the study contribute to the emerging field of low-rise rapid construction methods. The Automated Construction System (ACS) developed in this study is similar to the 'ground factory - building push-up' system (Bock and Linner, 2016b). However, the current method is used to build the structural frame of low-rise buildings. It is a modular construction method and uses light construction equipment, unlike the 'building push-up' system.



[1]HUS-ML: Hybrid Unsupervised and Supervised Machine Learning

Figure 1.2 Research objective: Development of a framework for identification of operations and faulty conditions in automated construction

1.3 SIGNIFICANCE OF THE STUDY

The idea of automated construction monitoring dates back to several decades (Sacks *et al.*, 2002). Emerging technologies have been explored for monitoring various construction resources (Roberts and Golparvar-Fard, 2019; Chen *et al.*, 2020; Langroodi *et al.*, 2021). However, the construction industry is still in the early stages of implementing automated equipment monitoring. Several pilot studies from actual construction sites have been reported from various parts of the world; some examples from the USA can be seen in (Fard, 2021).

Construction monitoring using sensor data involves several challenges, such as designing an optimal sensor configuration and data interpretation. There have been several studies on sensor placement, both in construction and other domains. For example, see (Papadopoulou *et al.*, 2016; Yu *et al.*, 2018; Goyal *et al.*, 2019; Mahami *et al.*, 2019; Mahjoubi *et al.*, 2020; Pachón *et al.*, 2020). The current study proposes a method to determine optimal sensor configuration for automated construction monitoring. While challenges related to sensor placement are not fully solved yet, greater challenges exist in data interpretation. Whether construction activities can be accurately identified using sensor data is an interesting question.

The three major components of an automated construction monitoring system are operation identification, operation tracking and performance estimation (Sherafat *et al.*, 2020). The present study addresses the operation identification and fault detection components essential for the development of a monitoring system. Generally, kinematic measurements, sound, images or videos of the construction equipment are collected for activity recognition. The present study uses the vibration data from the structure for operation identification. While there are several model-based methods like system identification (Goulet *et al.*, 2013; Soman *et al.*, 2017) for estimating the actual condition from sensor data, the model-free method based on machine learning (Golparvar-Fard *et al.*, 2013; Ahn *et al.*, 2015) is adopted for this study.

The current study focuses on developing a monitoring framework for low-rise automated construction systems. Operation identification and fault detection are some of the critical tasks in an automated monitoring system (Sherafat *et al.*, 2020). The monitoring system must identify operations in progress and possibly discern faulty operations to warn the operator on time. To identify faulty operations, precise identification of the operating states is necessary. The initial stage of this research focuses on identifying the normal operations followed by detection of faults in an Automated Construction System. Finally, the HUS-ML (Hybrid Unsupervised and Supervised Machine Learning) framework is developed by combining operation identification and fault detection methodologies.

The Automated Construction System developed for this study is for the construction of low-rise buildings (Harichandran *et al.*, 2020b). However, the monitoring framework proposed in this study can be applied to traditional, automated or robotic construction (Figure 1.1). Sensors measuring structural responses are installed on the structure during the construction. The interactions between labour, materials, equipment, and the structure will be reflected in the structural responses. These responses reveal the operation being carried out. Deviations from the normal responses are used to estimate the faulty conditions. This is the central idea of the operation identification and fault detection framework proposed in this study (Harichandran *et al.*, 2018, 2019b, 2019a, 2021).

The HUS-ML (Hybrid Unsupervised and Supervised Machine Learning) framework is most beneficial for the operators of automated equipment in the construction work. It helps them to ensure the safety and stability of the structure being constructed. For example, consider the coordinated lifting operation in an Automated Construction System. During coordinated lifting, all supports should lift simultaneously to move the structure upwards. Suppose one of the supports moves faster due to some internal error in the machine. A part of the structure will be lifted faster than the other and eventually overturn the entire structure. Situations like these will cause catastrophic accidents in real construction scenarios. Hence the monitoring system should be trained to recognise each activity accurately to detect any early signs of anomalies. Early signs in the current study refer to the 'early signs' in the pattern of the sensing data that indicates deviation from normal operations, detected using an anomaly detection algorithm. It is not referring to a warning sign for action. However, warning signs can be given to the operator based on the faulty condition detected. This data corresponding to the anomalous pattern ('early signs') is further analysed using the HUS-ML algorithm to extract more information about the faulty condition. Based on the available information on the type and location of the fault, the operator can take appropriate corrective actions.

The final goal is to develop an integrated automated construction monitoring system. Such a system will provide real-time information about all the construction activities. This will help to ensure the correct execution of the operations. Even though the identification framework is validated on a top-down construction case study here, it can be applied to any type of construction system. However, the hierarchy of learning tasks varies with the chosen construction method.

The proposed operation identification and fault detection framework is novel in several aspects compared to existing methods. Early detection of faults is necessary for accident mitigation in automated construction. The monitoring framework proposed in the study detects early signs of failure during operation. Besides, the model-free method of fault detection based on machine learning identifies known and unknown categories of faulty operations.

1.4 THESIS OUTLINE

The objectives of this research are addressed in nine chapters of this thesis. A brief description of the contents of each chapter is given below.

- Chapter 2 presents the review literature related to automated construction monitoring. This includes studies on Automated Construction Systems, activity recognition of construction equipment, fault detection methods, and measurement system design. In addition to that, a brief introduction to machine learning and deep learning methods are also included.

- Chapter 3 describes the methodology of the research. This chapter starts with an overview of the research methodology, followed by a detailed description of how each objective is achieved. Besides, the experimental evaluation of the developed framework is provided.

- Chapter 4 presents the theoretical framework and algorithms developed in the study. The HUS-ML framework and algorithms are introduced first, followed by the methodologies developed for sensor placement and operation identification.

- Chapter 5 contains the description of the experimental evaluation of the developed framework and algorithms. Initially, the automated construction method adopted in the study is described. Then the experimental setup, experiments, data collection and pre-processing are presented.

- Chapters 6 to 8 present the analysis of the experimental data and discussion on the results. Chapter 6 focuses on the evaluation of the sensor placement methodology, while chapter 7 on the operation identification methodology. Chapter 8 covers the validation of the HUS-ML framework.

- Chapter 9 concludes the thesis with significant outcomes. This chapter starts with a summary of the study followed by conclusions, contributions and limitations of the research

CHAPTER 2

REVIEW OF LITERATURE

2.1 INTRODUCTION

This chapter presents a review of literature that covers various aspects of automated construction monitoring. The current study is interdisciplinary research that contributes towards the theory of computing applications in construction. The background knowledge in the state-of-the-art automated construction methods is necessary to set the context of this study. Therefore, an overview of existing Automated Construction Systems and monitoring methods are described in Section 2.2. Subsequently, machine learning and deep learning algorithms applied are briefly described in Section 2.3 and Section 2.4. This section is followed by the description of the existing studies on construction equipment activity recognition in Section 2.5. Then, fault detection methods for machine and construction equipment are presented in Section 2.6, followed by the studies on measurement system design in Section 2.7. Finally, a summary of the reviewed literature and gaps in the research are presented in Section 2.8.

2.2 AUTOMATED CONSTRUCTION SYSTEMS

Even though automated construction systems were not widely adopted in the construction industry, it has been successfully implemented in several high rise construction projects in Japan (Cai *et al.*, 2019). However, a few of the studies related to these projects were disseminated in academic publications. Bock and Linner present a comprehensive analysis of ACS and classify them based on the construction scheme (Bock and Linner, 2016b). The main operation unit of the ACS is referred in the literature as ‘factory’. If the factory is located at ground level during construction, it is called the ground factory. If the factory is placed on the top of the building under construction and sequentially lifted with the progress of construction, it is termed the sky factory.

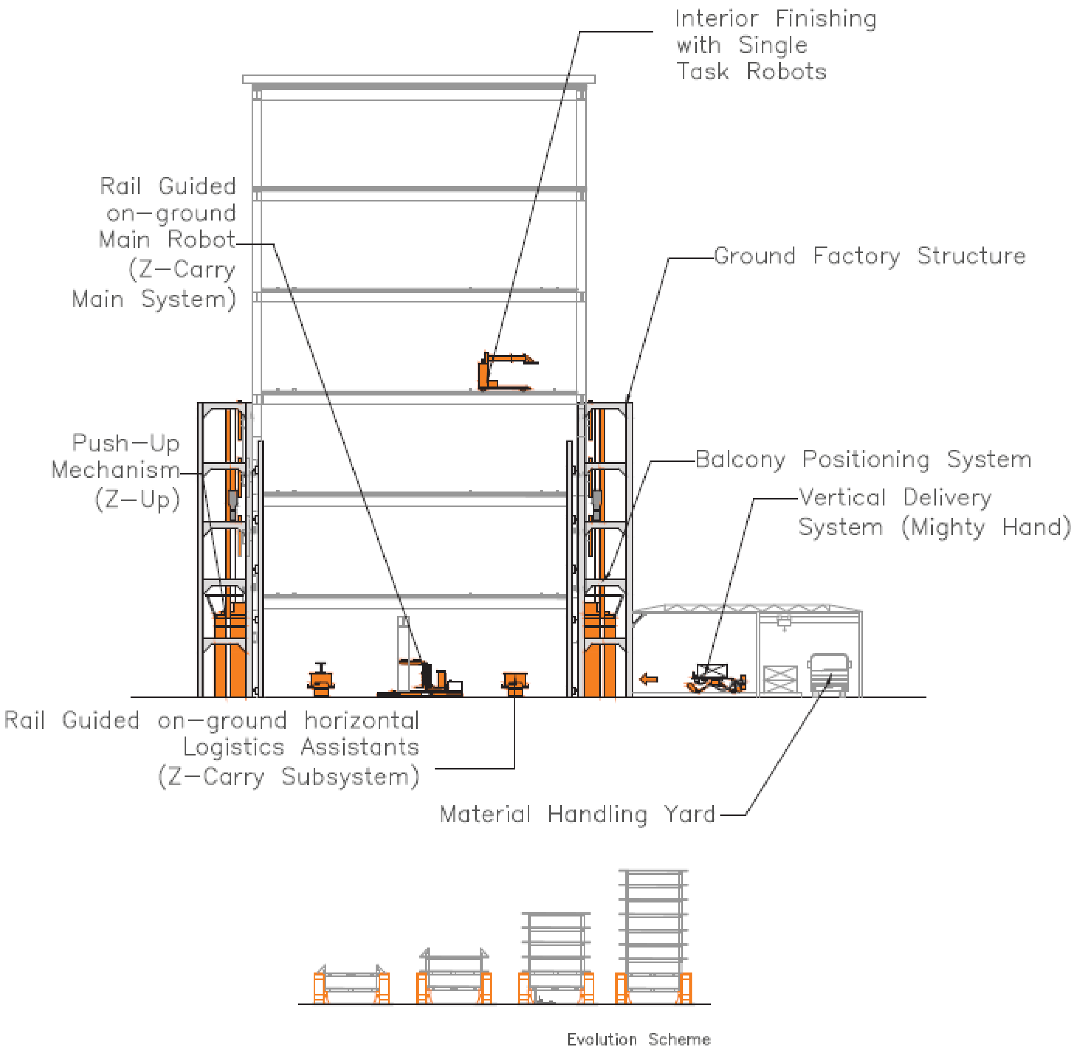


Figure 2.1 Subsystems, components and evolution scheme of Automatic Up-Rising Construction by Advanced Technique (AMURAD), developed by Kajima Corporation, Japan (Bock and Linner, 2016b)

2.2.1 Ground factory systems

The ground factory systems are categorised into three: 1) fixed ground factory that pushes the buildings up, 2) combined on-site and off-site factory, and 3) horizontally moving self-supported factory (Bock and Linner, 2016b). The construction progress from the top floor to the bottom floor in ground factory systems with building push-up method. The floors will be completed at the ground level and lifted upwards while the ground factory remains in a fixed location. The orientation of the buildings is vertical in high-rise buildings (for example, AMURAD) and horizontal in low-rise buildings (for example, System Skanska and J-up). Automatic Up-Rising Construction by Advanced Technique (AMURAD) is a ground factory system developed by Kajima Corporation, Japan (Sekiguchi *et al.*, 1997). The subsystems, components and evolution scheme of AMURAD is illustrated in Figure 2.1. The ground factory occupies the first four floors. It contains subsystems such as push-up mechanism (Z-Up), main robot (Z-carry main system), robots for horizontal logistics (Z-carry subsystem), vertical delivery system (Mighty hand) and other subsystems for material handling, storage and monitoring. The completed floors were pushed upwards by ten automatic controlled jacks (Z-Up), each having the capacity in the range of 400 tons to 600 tons. The AMURAD was used to construct high-rise concrete structures up to 20 floors high. Besides, implementation of AMURAD achieved an overall 20 per cent reduction in workforce, a 50 per cent reduction in industrial waste and 20 per cent reduction in construction time.

The ground factory systems with a building push-up method developed for low-rise construction (System Skanska and J-up) comprise more simple sub-systems than high-rise construction (AMURAD). These systems build long horizontally oriented residential buildings. The System Skanska developed by Skanska Group, Sweden deploys rail-guided robots similar to that of AMURAD for assembling the building components (Bock and Linner, 2016b). However, the building components are comparatively heavier and larger. The subsystems consist of a fixed ground factory, lifting system, assembly robots, controlling system, and systems for delivering, handling, and storing materials. First, the ground factory and assembly robots are installed at the ground level. Then each floor is assembled at ground level and sequentially lifted using the lifting system until the completion of the building. The lifting system comprises heavy-duty hydraulic cylinders capable of lifting heavy concrete floors. The System Skanska reduces construction complexity by standardising 80 percentage of the concrete building components.

Another low-rise construction system that adopts the ground factory with building push-up method is the J-up system developed by Sekisui House, Ltd., Japan (Bock and Linner, 2016b). This is a simple and cost-effective system for constructing residential buildings up to three floors high. The J-up system comprises two main subsystems: 1) hydraulic jacks for pushing the building up and 2) steel frames for supporting the structure temporarily. This construction system also starts by constructing the roof and temporarily supporting it on the structural frame. The completed roof is then lifted using the hydraulic jacks through a computer aided control system. The lower floors are constructed and lifted one by one in a similar manner. The building components are prefabricated in an off-site automated factory and supplied to the construction site. The process of pushing up the building is automated in the J-up system, while the building components are connected manually. This avoids the use of heavy and complex rail-guided mechanisms resulting in a considerable cost reduction. Besides, the flexibility of construction is increased since the building configuration can be varied by the placement of the hydraulic jacks.

The second category of ground factory systems implemented for low-rise construction is combined on-site and off-site factory systems. NCC Komplett, developed by NCC, Sweden belongs to this category; this system involves the synchronised operation of two factories (Bock and Linner, 2016b). The on-site factory consists of a self-supporting hall structure that provides weather protected environment and subsystems for handling and connecting high-level building components. The off-site factory prefabricates and finishes concrete building components and transports them to the on-site factory through delivery trucks. The finished products are delivered just in time and just in sequence for assembly. Good coordination between the two factory units is essential for this system. The maximum allowable height of the building was limited by the on-site factory structure to eight floors.

The third ground factory system, the horizontally moving self-supported factory, is mainly developed for long horizontally oriented buildings. The ground factory covers the structure and moves horizontally on a rail with construction progress. These systems belong to the mechanized category rather than automated systems. Some examples of these systems include Bauhelling Summerfield developed by AHAG-Sommerfeld, Germany and; Bauschiff developed by Neufert, Germany (Bock and Linner, 2016b). The ground factory system has several advantages and ease of construction since the main operations are performed at the ground level. However, the building height is limited by the capacity of the lift-up systems. The sky factory systems surpass this issue.

2.2.2 Sky factory systems

The majority of the ACS implemented in high rise construction belong to the sky factory systems. These systems follow a variety of construction schemes. In most sky factory systems, the factory is supported by the building under construction and moves upwards as the work progresses. Automated structural steel Building Construction System (ABCS) developed by Obayashi, Japan (Wakisaka *et al.*, 2000) and Shimizu Manufacturing System by Advanced Robot Technology (SMART) developed by Shimizu, Japan (Yamazaki and Maeda, 1998) are some of the examples. In another construction scheme, the sky factory is supported by stilts of its own independent of the building structure. The sky factory provides a weatherproof working environment like the earlier construction scheme. However, the synchronisation of construction works was simplified since the sky factory moves upwards on the extending stilts instead of supported by the structure. BIG CANOPY developed by Obayashi, Japan (Hamada *et al.*, 1998) is an example.

Figure 2.2 A view of the sky factory construction system BIG CANOPY developed by Obayashi Corporation, Japan (Bock and Linner, 2016b)

The third construction scheme involves a sky factory and a core factory, both moving upwards with the construction progress. The sky factory is pulled upwards along the core structure, which is built in advance by the core factory. Robotic and Crane based Automatic Construction System (RCACS) developed by Korean Consortium, South Korea, belong to this construction scheme (Kang *et al.*, 2011). The core factory with limited functionality follows a simple construction scheme for building the structural core. The main sky factory deals with significant construction operations. Other categories of sky factory systems include a combination of conventional construction and centralized or decentralized sky factories (Bock and Linner, 2016b).

2.2.3 Monitoring in Automated Construction Systems (ACS)

The development and testing of a new ACS demand high investment in terms of time and cost, along with coordination between academic, industrial and interdisciplinary subject experts. Hence most of the existing research and developments in ACS is mainly for high rise construction (Bock and Linner, 2016b, 2016a; Cai *et al.*, 2019). In a comprehensive analysis of ACS presented by Bock and Linner, only five out of the thirty Automated Construction Systems are developed for low-rise buildings (Bock and Linner, 2016b). Two out of these five construction systems are historical prototypes of mechanised construction rather than automated construction. System Skanska, J-up and NCC Komplett are the remaining three low-rise Automated Construction Systems. Each of these ACS has automated subsystems and associated control systems for assembly or lifting of building components. However, none of them has a real-time monitoring system. System Skanska and NCC Komplett have heavy machinery for handling, manipulating, and lifting building components. Therefore, accident potential and implementation costs are higher than the J-up system. In the context of rapidly rising demand for economic ACS for low rise construction, the author of this study has developed an automated top-down construction system with others (Raphael *et al.*, 2016; Harichandran *et al.*, 2019b, 2019a, 2020b, 2020a, 2021). It has developed incrementally through laboratory prototypes, introducing higher complexity at each development stage. This ACS aims to incorporate an integrated monitoring system for ensuring safety.

Table 2.1 Monitoring systems in Automated Construction Systems (ACS)

Reference	ACS	Company	Construction scheme(Bock and Linner, 2016b)	Realtime monitoring system	Monitoring system components
(Hamada *et al.*, 1998)	BIG CANOPY	Obayashi	Sky Factory moving upwards on supports	Yes	Simulation and optimization software, barcode
(Wakisaka *et al.*, 2000)	Automated structural steel Building Construction System (ABCS)	Obayashi	Sky Factory moving upwards supported by the structure	Yes	Sensor system, cameras, barcode
(Sekiguchi *et al.*, 1997)	Automatic Up-Rising Construction by Advanced Technique (AMURAD)	Kajima	Ground Factory and building push-up	Yes	Sensors, control room
(Yamazaki and Maeda, 1998)	Shimizu Manufacturing System by Advanced Robot Technology (SMART)	Shimizu	Sky Factory moving upwards supported by the structure	Yes	Bar code, laser, control room, simulation and optimization software
(Kang *et al.*, 2011)	Robotic and Crane based Automatic Construction System (RCACS)	Korean Cons.	Sky Factory pulled up along core	Yes	Sensor-based real-time progress and visualisation system

The ACS for high rise construction is extremely complex and contains several intricate subsystems such as factory (or centralised operation unit), manipulators, climbing mechanisms, and real-time monitoring and management system (RTMMS). Each subsystem focuses on a particular construction task, and only a few of them are introduced with automated monitoring. The development and deployment of RTMMS require a high investment of money and computing resources that are often infeasible for low-rise construction systems. Since low-rise, ACS has a fairly simple configuration and developing an overall automated monitoring system that covers the entire construction activities is highly feasible. This integrated monitoring enables better control over the overall construction process and improves the efficiency of the ACS (Harichandran *et al.*, 2019b, 2019a, 2020a). The current study focuses on recognising the automated construction activities and faults, which is an integral part of developing an automated monitoring system.

The RTMMS in a few of the Automated Construction Systems consists of a fully computerised on-site control centre. Table 2.1 lists some of the Automated Construction Systems and the monitoring systems adopted in them. The components of the monitoring system involve sensors, cameras, barcodes, control room, laser, RFID and software for data collection and analysis (Sekiguchi *et al.*, 1997; Tanijiri *et al.*, 1997; Yamazaki and Maeda, 1998; Wakisaka *et al.*, 2000; Ikeda and Harada, 2006). Some of the current ACSs lack real-time monitoring systems (Gassel, 2005; Bock and Linner, 2016b). However, the monitoring in other ACSs is usually performed for checking whether specific tasks have been completed successfully. Most construction systems have independent sub-systems focusing on designated tasks like material handling, assembling, lifting, etc. (Kang *et al.*, 2011). Hence, collecting integrated information about the whole automated construction is highly challenging are often not explored in existing ACS. This information is crucial for critical decision making, especially to avoid major accidents (Harichandran *et al.*, 2019a). More details on the fault detection methods implemented in these RTMMS are the intellectual property of the companies that developed them and are often unavailable in published literature (Bock and Linner, 2016b, 2016a; Cai *et al.*, 2019). Besides, none of the existing low-rise ACS has a real-time monitoring system (Bock and Linner, 2016b). Since the studies on monitoring of low-rise ACS were unavailable, the studies on monitoring of construction equipment were explored (section 2.5 and section 2.6).

Machines in automated or robotic construction should not be entrusted to make logical decisions when there are significant uncertainties in situations that are likely to cause accidents. A human operator can act better in those scenarios. However, software systems are better equipped for discerning minute variations in patterns of construction-related data (Harichandran *et al.*, 2019b). If the meaning of these patterns is readily interpretable, humans can take quick decisions based on the circumstances. This is why an integrated automated monitoring system with a human operator will have better control over overall construction than discrete construction sub-systems. Unlike high rise ACSs with numerous sub-systems, developing an integrated monitoring system for low-rise automated construction is feasible. Presently, there are limited studies in this area. The authors of the current study have developed an ACS for low-rise building construction (Harichandran *et al.*, 2019b, 2019a, 2020b). Identifying the basic operations of the ACS is the primary step in the development of an automated monitoring system. Integrated information about the construction process can be obtained from sensor measurements taken from either the structure under construction (Harichandran *et al.*, 2019b) or the construction equipment (Soman *et al.*, 2017). The present study attempts to identify the operations of an ACS from the sensor data collected from the structure and extends it further to detect faulty conditions. This approach is applicable to automated and robotic constructions involving different scenarios such as site factories and single or multiple robots on site. The construction operation can be identified irrespective of the construction method since the interaction of the robots and the structure will create structural responses with characteristic patterns. This study uses these patterns to identify normal operations and early signs of faulty conditions during automated construction.

2.3 MACHINE LEARNING

Machine learning techniques, in a broad context, extract meaningful information from data. These techniques have gained increasing attention due to the advent of high computing capacity and the availability of large datasets. The machine techniques can be classified into two categories: supervised learning and unsupervised learning. Supervised learning techniques use examples of input and corresponding output to generate predictive models, while unsupervised learning techniques determine inherent patterns in the input data. Supervised learning can be applied for developing predictive models for classification or regression. The classification models predict discrete outcomes to categorise the supplied data into various classes, whereas regression models predict continuous outcomes to forecast future trends.

2.3.1 Classification algorithms

The current study applies supervised learning algorithms to recognise automated construction operations. An overview of the classification algorithms used in the study is discussed in this section; for detailed descriptions, refer (Mitchell, 1997; Bishop, 2006; Shalev-Shwartz and Ben-David, 2014).

2.3.1.1 k-Nearest Neighbour (kNN)

A data point is classified based on its similarity with the nearest neighbours. More neighbouring samples are considered for predicting the class label to avoid potential misclassifications due to outliers. This algorithm does not assume that the data from each class are generated through some underlying statistical distributions. Therefore, it develops a simple model for prediction.

2.3.1.2 Decision Tree (DT)

The decision trees predict the labels of data points based on a set of rules. The decisions are made through various branching conditions to reach the leaf node of the tree from the root node. The configuration of the decision tree and weights for comparison are estimated during training. The developed model can be simplified by 'pruning' the decision tree. The prediction models are easily interpretable.

2.3.1.3 Support Vector Machines (SVM)

This algorithm separates the classes in a binary classification problem through a linear decision boundary (discriminant or classifier). The discriminant is a hyperplane when the algorithm separates a high dimensional dataset. The optimal hyperplane for a linearly separable dataset is the discriminant that provides the maximum margin between the classes. This discriminant has the highest distance to the nearest training datapoints. This algorithm classifies the linearly inseparable data points through the introduction of a penalty function. Kernel functions are used in nonlinear classification to transform the data into a high dimensional feature space, where linear separation is possible.

2.3.1.4 Discriminant Analysis (DA)

This algorithm determines the discriminant between the classes by assuming each class follows a Gaussian distribution for data generation. The multidimensional normal distribution of each class is estimated by computing the mean and covariance matrix. The decision boundary is determined through the data points with equal probability for the adjacent classes. If the classes are assumed to have the same covariance matrix, the decision boundary is linear; otherwise, it is quadratic. The algorithm develops robust models since the decision boundary is determined through the distribution of all classes.

2.3.1.5 Naïve Bayes (NB)

Similar to discriminant analysis, the Naïve Bayes algorithm assumes that the data from each class are generated through a probability distribution. Therefore, the class label is predicted based on the probability of the data point to occur in a specific class. The algorithm also assumes that the predictors are independent, and the distribution of each predictor is calculated independently. The predictive model indicates the confidence of the classification and is robust to noise.

2.3.1.6 Artificial Neural Network (ANN)

Artificial Neural Network creates a predictive model that comprises several interconnected neurons to map the relationship between input and output. The strength of the connections is controlled by the numeric values known as weights. The weights of the neural network are iteratively modified during training to improve the performance of prediction. Feed-forward classification networks are used for classification problems. The network architecture comprises the input layer, hidden layer and output layer; each layer consists of multiple interconnected neurons. The output from each neuron influences the input to the succeeding neurons connected to it.

The input to each neuron is computed by applying a transfer function to the sum of the product of the output of the predecessor neurons and their weights offset by the biases. The values of the weights and biases are learned during training.

2.3.2 Anomaly detection

An anomaly detection algorithm is an unsupervised learning algorithm that identifies abnormal values in a dataset based on statistical measures. Creating an anomaly detection model starts with fitting a Gaussian model to the distribution of the normal data points. The unlabelled data set for training, *{d(1), ..., d(m)}* contains only examples of the normal class, where *m* is the number of training instances. The Gaussian distribution for each feature *di* has to be estimated for the training dataset as given by Equation (2.1).

$$p(d; \mu, \sigma^2) = \frac{1}{\sqrt{2\,\pi\,\sigma^2}} e^{-\frac{(d-\mu)^2}{2\,\sigma^2}} \tag{2.1}$$

The parameters of the Gaussian distribution, mean and variance denoted by μ and $\boldsymbol{\sigma^2}$, are computed as given by Equations (2.2) and (2.3) to fit data in the i^{th} dimension.

$$\mu_i = \frac{1}{m} \sum_{j=1}^{m} d_i^{(j)} \tag{2.2}$$

$$\sigma_i^2 = \frac{1}{m} \sum_{j=1}^{m} \left(d_i^{(j)} - \mu_i\right)^2 \tag{2.3}$$

After estimating the Gaussian parameters, the probability of each data point in the fitted distribution can be calculated. The data points with very low probability tend to be anomalous observations. A threshold is selected based on a cross-validation dataset to determine these anomalous observations.

Let $\{(d_{cv}^{(1)}, l_{cv}^{(1)}), \dots, (d_{cv}^{(m_{cv})}, l_{cv}^{(m_{cv})})\}$ be the labelled cross-validation dataset where $(d_{cv}^{(i)}, l_{cv}^{(i)})$ denotes the i^{th} data point and corresponding label, and m_{cv} denotes the number of instances in the cross-validation dataset. Anomalous observations in this dataset are labelled as one, and normal observations are labelled as zero. Then the probability of each data point in the cross-validation dataset $p(d_{cv}^{(i)})$ is computed. If $p(d_{cv}^{(i)})$ is less than the selected threshold, T then it is considered as an anomalous observation. The probability vector for the cross-validation dataset $p(d_{cv}^{(1)}), \dots, p(d_{cv}^{(m_{cv})})$ is compared with the ground truth label set $l_{cv}^{(1)}, \dots, l_{cv}^{(m_{cv})}$ and the F1 score is computed by Equation (2.4). The F1 score shows the fault detection performance with the given threshold T. Different values of T were applied on the cross-validation dataset, and F1 scores were computed to determine the best value of T. The selected threshold T is used to determine the anomalous observations in future predictions.

$$F1\ score = \frac{2\ x\ Precision\ x\ Recall}{Precision + Recall} \tag{2.4}$$

2.4 DEEP LEARNING

Deep learning is a subcategory of machine learning where deep neural networks are used for facilitating end-to-end learning. This means that deep learning algorithms directly learn required information from raw data for performing the assigned task. The current study uses Long Short-Term Memory (LSTM) networks for time series data classification.

2.4.1 Long Short-Term Memory Networks

Long Short-Term Memory (LSTM) networks identify long term dependency between timesteps of sequence data (Hochreiter and Schmidhuber, 1996, 1997; Hochreiter, 1998; Arras *et al.*, 2019). They belong to the class of Recurrent Neural Networks (RNN). The architecture of an LSTM network for a classification problem consists of five layers. The first layer is a sequence input layer that inputs the raw sequence data into the network. The second layer is an LSTM layer which learns the long-term dependency between timesteps of the input data. The last three layers, namely, the fully connected layer; SoftMax layer; and classification layer enable the network to predict the class labels.

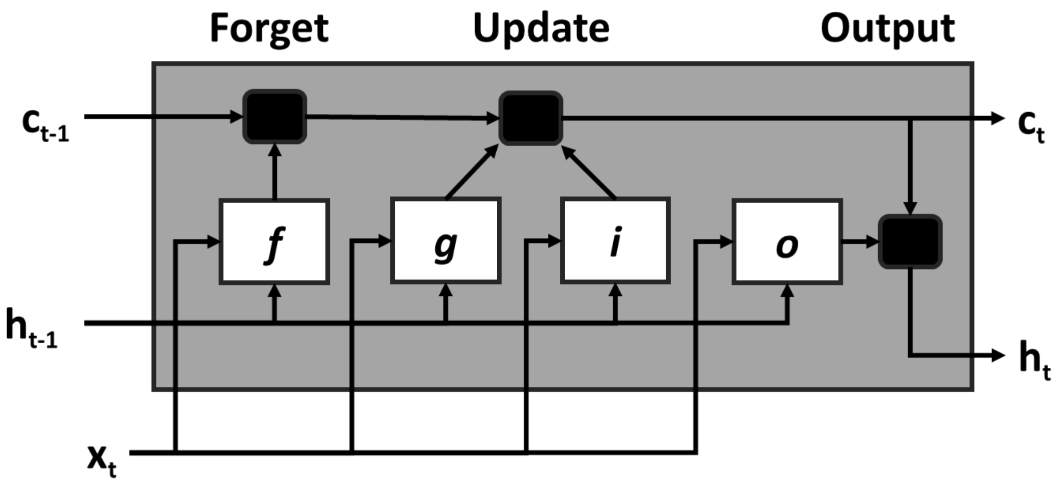


Figure 2.3 Information flow in an LSTM block (Hochreiter and Schmidhuber, 1997)

The LSTM layer consists of several LSTM blocks; the flow of information through a block is illustrated in Figure 2.3 (Hochreiter and Schmidhuber, 1997; MATLAB & Simulink, 2021). Hidden state (h_t) and cell state (c_t) constitute the state of the layer at timestep t, and x_t denotes the value of the time series at timestep t. The hidden states and cell states are controlled by the components such as input gate (i), forget gate (f), cell candidate (g), and output gate (o). The update and reset of the cell state are controlled by the input gate and the forget gate, respectively. The information to the cell state is added by the cell candidate, while information of the cell state to the hidden state is controlled by the output gate. Each of these components can be computed as given in (2.5) to (2.8).

$$i_t = \sigma_g(W_i\, x_t + R_i\, h_{t-1} + b_i) \tag{2.5}$$

$$f_t = \sigma_g(W_f\, x_t + R_f\, h_{t-1} + b_f) \tag{2.6}$$

$$g_t = \sigma_c(W_g\, x_t + R_g\, h_{t-1} + b_g) \tag{2.7}$$

$$o_t = \sigma_g(W_o\, x_t + R_0\, h_{t-1} + b_o) \tag{2.8}$$

where W, R and b denote the concatenation of the matrices of the learnable weights such as input weights, recurrent weights and bias of all the components (i,f,g,o). The state activation function and gate activation function are represented by σ_c and σ_g.

2.5 ACTIVITY RECOGNITION OF CONSTRUCTION EQUIPMENT

In most of the studies, construction equipment is monitored for calculation of cycle time, productivity, cost and fuel consumption, or for optimally allocating resources. In such cases, minor mistakes in identification are not critical. Since this work aims to develop an automated monitoring system for the safe operation of construction equipment, the expected accuracy of identification is high. Majority of existing equipment activity identification methods use computer vision, sensor data, audio data, or other characteristic measurements from the equipment. Table 2.2 and Table 2.3 summarise various equipment activity recognition methods and their performances. The methods are subdivided based on the data collected for identification (visual data, sensor data and audio data). The following paragraphs further examine each of these activity recognition methods and their applicability for identification of automated construction operations.

Table 2.2 Overview of equipment activity identification systems

Reference	Purpose of activity identification	Equipment	Data collected	Testing environment	Number and type of activities
Activity recognition based on visual data					
(Golparvar-Fard *et al.*, 2013)	For automating construction activity analysis	Excavator and truck	Videos	Actual construction site	Excavator: 3 (digging, dumping, hauling / swinging); Truck: 3 (filling, moving, dumping)
(J. Kim *et al.*, 2018)	Estimating cycle time and equipment productivity	Excavator and dump truck	Images	Actual construction site	3 (stopping, moving, scooping/ rotating/ dropping)
(Kim and Chi, 2019)	Estimating cycle time and equipment productivity	Excavator	Images	Actual construction site	4 (digging, hauling, dumping, swinging)
(Roberts and Golparvar-Fard, 2019)	Estimating equipment productivity	Excavator and dump truck	Videos	Actual construction site	Excavator: 5 (idle, swing bucket, load bucket, dump, move); Dump truck: 2 (fill, move)

(Chen *et al.*, 2020)	Estimating equipment's operation time, operating cycle and productivity.	Excavators	Videos	Actual construction site	3 (digging, swinging, loading)
Activity recognition based on sensor data					
(Ahn *et al.*, 2015)	Estimating environmental performance and equipment operational efficiency	Excavator	Acceleration data	Instructed operations in an actual construction site (sensors inside the equipment cabin)	3 (engine-off, idling, working modes)
(Akhavian and Behzadan, 2015)	Estimating activity duration for simulation input modelling	Front-end loader	Acceleration data, Gyroscope data and Positional data (GPS)	Actual construction site (smartphone (built-in smartphone sensors) inside equipment cabin)	At classification level 2: 3 (engine off, idle, busy); At classification level 3: 4 (engine off, idle, moving & scooping, moving & dumping); At classification level 4: 5 (engine off, idle, moving, scooping, dumping)

(Hyunsoo Kim *et al.*, 2018)	Estimating equipment cycle time	Excavator	Inertial Measurement Unit (IMU) data	Actual construction site (smartphone (built-in smartphone sensor) inside equipment cabin)	5 (idle, wheelbase motion, cabin rotation (anti-clockwise and clockwise rotation), bucket/arm movement)
(Rashid and Louis, 2019)	Estimating the performance of equipment	Excavator and front-end loader	IMU data	Actual construction site (sensors on different articulated parts of the equipment)	Excavator: 9 (engine off, idle, scoop, dump, swing loaded, swing empty, move forward, move backwards, level ground); Front-end loader: 10 (engine off, idle, scoop, raise, dump, lower, move forward loaded, move backwards loaded, move forward empty, move backwards empty)
(Shi *et al.*, 2020)	Estimate the working cycle stages of equipment for energy	Excavator	Main pump pressure and displacement data	Instructed operations (pressure sensors on main pump	5 (pre-digging, digging, lifting, unloading, swinging)

	and fuel efficiency.			outlet, displacement sensors on rod chamber of the boom, arm, and bucket cylinders)	
(Slaton *et al.*, 2020)	Estimating equipment productivity	Roller compactor and excavator	Acceleration data	Actual construction site (sensors on arms and inside equipment cabins)	Compactor: 6 (combinations of forward and backward movements with 3 vibration modes); Excavator: 7 (idling, travelling, scooping, dropping, rotating (left), rotating (right), various)
Activity recognition based on sound data					
(Cao, Huang, *et al.*, 2017)	Equipment recognition for surveillance system	4 machines (Electric hammers, hydraulic hammers, cutting machines, and excavators)	Audio data	Actual construction site (microphone sensors in proximity to the equipment)	5 (Activities of electric hammers, hydraulic hammers, cutting machines, engine of cutting

					machine, and excavators)
(Cao, Wang, *et al.*, 2017)	Equipment recognition for surveillance system	4 machines (Electric hammers, hydraulic hammers, cutting machines, and excavators)	Audio data	Actual construction site (microphone sensors in proximity to the equipment)	4 (Activities of electric hammers, hydraulic hammers, cutting machines, and excavators)
(Cao, Zhao, *et al.*, 2017)	Equipment recognition for surveillance system	4 machines (Electric hammers, hydraulic hammers, cutting machines, and excavators)	Audio data	Actual construction site (microphone sensors in proximity to the equipment)	4 (Activities of electric hammers, hydraulic hammers, cutting machines, and excavators)
(Cheng *et al.*, 2017)	Estimating equipment productivity and activity analysis	11 different types of machines	Audio data	Actual construction site (microphones in proximity to the equipment)	2 (major activity, minor activity; identifying operations of one machine at a time)
(Sabillon *et al.*, 2018)	Estimating cycle time of equipment	Multiple machines	Audio data	Actual construction site (microphones	2 (major activity, minor activity)

				in proximity to the equipment)	
(Cheng *et al.*, 2019)	Estimating cycle time and equipment productivity	Multiple machines	Audio data	Actual construction site (microphones in equipment cabin and in proximity to the equipment)	2 (major activity, minor activity)

With the advent of low-cost recording devices and better computing platforms, computer vision-based methods of activity identification become extremely popular. Golparvar-Fard et al. (Golparvar-Fard *et al.*, 2013) used Spatio-temporal features from video recordings to identify activities of excavator and dump truck with Support Vector Machines (SVM). They focus on identifying the single actions of earthmoving equipment. The problems due to noisy feature points, varied background, poses of equipment and levels of occlusion were addressed. Kim et al. (J. Kim *et al.*, 2018) included the interactions between excavators and dump trucks to identify their operations by a method called tracking-learning-detection. They showed that the incorporation of domain knowledge in problem formulation considerably improved the identification accuracy. Kim and Chi (Kim and Chi, 2019) considered the sequential working pattern of excavators for improving vision-based action recognition. They have used a hybrid of two deep learning methods for classification. The activities of heavy equipment and labours were identified by the bag-of-video-feature-words framework and overcame the limitations of variations in scale, partial obstruction and point of view (Gong *et al.*, 2011). All of these methods show promising results. However, the construction site is a complex environment with various disturbances and obstructions. The dynamic nature of operations cannot be fully captured by still cameras (Sherafat *et al.*, 2020). The applicability of computer vision-based methods is limited in this aspect. Most of these studies identify activities of earth excavation or moving equipment. This equipment has articulating parts or movements which can be clearly captured through visual data. Identification of minute variations in the parts of equipment during various operations is extremely challenging by computer vision-based methods. Hence, activity recognition based on visual data will not be suitable for identifying operations of ACS.

Sensor-based activity recognition methods rely on a wide range of characteristic measurements from the equipment. Most popularly used data include acceleration or vibration, location of the equipment or a combination of these. Ahn et. al. (Ahn *et al.*, 2015) demonstrated the feasibility of using the low-cost accelerometer for identifying the operations of an excavator with machine learning classifiers and achieved 93% identification accuracy. Akhavian and Behzadan (Akhavian and Behzadan, 2015) used accelerometer and gyroscope data for predicting the operations of a front-end loader with machine learning classifiers. The identified operations were used to estimate the activity duration for simulation input modelling. Even though the identification of major classes of operations was highly accurate, the performance reduced while identifying finer classes. For cycle time measurement of equipment, Kim et. al. (Hyunsoo Kim *et al.*, 2018) used IMUs embedded in a smartphone. With the help of the dynamic time warping algorithm, they achieved 91.83% accuracy in cycle time estimation. Rashid and Louis (Rashid and Louis, 2019) placed inertial measurement units (IMUs) on the articulated part of the equipment to identify their operations using deep learning methods. The improvement of prediction results with various types and levels of data augmentation is explored in this study. Shi et. al. (Shi *et al.*, 2020) considered the working stages of an excavator and main pump pressure for operation identification. Instead of using complex deep learning methods, they have applied machine learning classifiers for identification. The domain knowledge is introduced in the problem formulation employing a rule-based intelligent calibration system to obtain a prediction accuracy of 93.82%. The location of the equipment and vibration patterns captured by sensors have the potential to identify operations better compared to limited visual data. The sensor-based activity recognition methods are capable of delivering high performance in real-time. Most of these methods are unaffected by ambient or climatic conditions. These serve as promising attributes for identification of automated construction operations.

Audio-based activity recognition methods are mainly suitable for equipment that produce significantly measurable sounds. Cheng et al. (Cheng *et al.*, 2017) used audio signals and SVM classifiers to identify various construction equipment activities. This method attempts to address the limitations of computer vision methods and sensor methods by capturing the sound patterns of heavy equipment to identify its activity. Similar studies have been carried out for equipment activity recognition using audio data as listed in the last sections of table 2 and 3. Audio-based methods can identify multiple machines at once. However, the level of details of the activities identified by these methods is minimal. Hence, audio-based activity recognition methods are not suitable for developing a monitoring system.

Table 2.3 Equipment activity identification methods and performance

Reference	Methods/Algorithms	Activity detector/ Features	Performance in activity identification
Activity recognition based on visual data			
(Golparvar-Fard *et al.*, 2013)	Support Vector Machine (SVM)	Spatio-temporal visual features represented by Histogram of Oriented Gradients (HOG)	Average accuracy for excavator 86.33%, for truck 98.33%
(J. Kim *et al.*, 2018)	Tracking-Learning-Detection (TLD)	Proximity threshold	Average precision 91.27% and average recall 92.42%
(Kim and Chi, 2019)	TLD, Hybrid deep learning algorithm (Convolutional Neural Network (CNN) and Double-layer Long Short-Term Memory (LSTM)) networks	Sequential patterns of visual features and operation cycles	Average accuracy 93.8%
(Roberts and Golparvar-Fard, 2019)	CNN, Hidden Markov Model (HMM), Gaussian Mixture Model (GMM), SVM	Spatio-temporal features	Average precision for excavators 97.43%, for dump trucks 75.29%; Accuracy for excavators 86.8%, for dump trucks 88.5%
(Chen *et al.*, 2020)	Faster R-CNN	Spatio-temporal features	Overall accuracy 87.6%
Activity recognition based on sensor data			
(Ahn *et al.*, 2015)	Naïve Bayes, kNN (K-Nearest Neighbour), Decision tree (J48), Multilayer	Totally 15 time-domain features (average resultant acceleration, mean, standard	Accuracy over 93%

	perceptron (feedforward ANN)	deviation (SD), peak, correlation)	
(Akhavian and Behzadan, 2015)	Logistic Regression (LR), kNN, Decision Tree, Neural Network (feed-forward backpropagation), SVM	Totally 42 features (Time domain features: mean, variance, peak, interquartile range (IQR), correlation, and root mean error (RMS), Frequency-domain feature: signal energy)	Overall accuracy 86.09% for the highest classification level
(Hyunsoo Kim *et al.*, 2018)	Dynamic Time Warping (DTW), Random Forest, Naive Bayes, J48, Sequential Minimum Optimization (SMO)	Totally 74 features (Time domain features: resultant, mean, SD and peak of acceleration, correlation, zero crossing rate, kurtosis, skewness, Frequency-domain features: spectral entropy, spectral centroid, short time energy, and spectral roll-off)	Overall accuracy 88.61%
(Rashid and Louis, 2019)	ANN, LSTM networks	18 features (3 IMUs X 6 data stream per IMU)	Accuracy for excavator 97.9%, for front-end loader 96.7%; F1 Score for excavator 97.6%, for front-end loader 96.3%
(Shi *et al.*, 2020)	SVM, Back Propagation Neural Network (BPNN), LR	6 features (Mean and variance of various combinations of main pump pressure signals)	Accuracy 93.82%

(Slaton *et al.*, 2020)	CNN, Hybrid network (CNN and LSTM)	6 features (2 accelerometers X 3 data stream per accelerometer)	Accuracy over 77% and up to 96% for compactor and up to 90% for excavator
Activity recognition based on sound data			
(Cao, Huang, *et al.*, 2017)	A newly proposed algorithm based on single hidden layer feedforward neural network and Extreme Learning Machine (ELM), Back Propagation (BP), KNN, SVM, ELM	MFCC (Mel-Frequency Cepstral Coefficients) features and their dynamic statistics	Accuracy over 40%, up to 88%
(Cao, Wang, *et al.*, 2017)	A newly proposed Cascade algorithm developed in MATLAB and LabView, ELM, SVM	Short frame energy ratio, concentration of spectrum amplitude ratio, truncated energy range, and interval of pulse	Accuracy over 86%, up to 99%
(Cao, Zhao, *et al.*, 2017)	BP, ANN using ELM	First and second order MFCC features	Accuracy over 74%, up to 96%
(Cheng *et al.*, 2017)	SVM	STFT features	Accuracy over 80%
(Sabillon *et al.*, 2018)	SVM	Frequency magnitude and phase features	Accuracy of cycle times as high as 90%
(Cheng *et al.*, 2019)	SVM	Sinusoidal frequency, magnitude, phase content	Accuracy over 85%

Previous research shows that the operations which involve the limited movement of equipment are best identified by sensor-based methods or by characteristic measurements from the equipment. Operations which involve machine vibrations are best captured by accelerometers. Development of an automated construction system requires a high level of detail about the operations. Sensor measurements have the potential to provide detailed information about the equipment. Among all the activity recognition methods, sensor-based methods seem to be the best option for identification of automated construction operations.

The existing methods identify high-level construction activities. However, the performance of these methods declines while identifying low-level operations. Most of the studies were focused on improving the performance, either through the type of data collected or by exploring multiple classification algorithms. This study explores the possibility of improving the performance of operation identification focusing on the problem formulation. The proposed methodology is not similar to the existing methods just because it applies machine learning algorithms. The current methodology is a much-improved version of the existing methods in the following aspects:

- Incorporating domain knowledge in operation identification
- Maintaining performance while identifying low-level operation details
- Detecting unknown faulty conditions with reasonable accuracy

2.6 FAULT DETECTION METHODS

Fault detection methods have been vastly studied in various domains such as manufacturing (Pu *et al.*, 2020; Quatrini *et al.*, 2020), electrical systems (De Santis *et al.*, 2018; Labrador Rivas and Abrão, 2020; Chen *et al.*, 2021), mechanical equipment (Alshorman *et al.*, 2020; Gangsar and Tiwari, 2020), High-Performance Computing (HPC) systems (Netti *et al.*, 2020), and heating, ventilation, air conditioning, and refrigeration (HVAC&R) systems (Gharsellaoui *et al.*, 2020; Ding *et al.*, 2021; Li *et al.*, 2021). A large quantum of monitoring data is available since the advent of low-cost sensing technologies. In addition to that, access to high computing resources shifted the focus of fault detection studies in every domain to data-driven methods using intelligent algorithms. The fundamental computing research focus on improving the learning algorithms and feature engineering (Pang *et al.*, 2021). While, applied research on fault detection in each domain focus on identifying the right algorithm and data (to be collected to extract more meaningful information) that improves the performance of detection (AlShorman *et al.*, 2021; Xu and Saleh, 2021). Detection of faults in mechanical and construction equipment are more relevant to the focus of this research. Therefore, these studies are explored in detail in the following sections.

2.6.1 Machine fault detection

Mechanical equipment is the backbone of most engineering fields such as manufacturing, aerospace, defence, and power sectors. Faults in mechanical equipment result in unanticipated downtime, enormous financial loss, disastrous accidents and severe injuries (Jiao *et al.*, 2019). Therefore, fault detection is a highly significant, widely explored and continuously emerging research area in machine condition monitoring. The current fault detection methods can be divided into four categories as per their development approach: 1) fault detection based on signal processing, 2) fault detection based on physical models, 3) fault detection based on machine learning, and 4) hybrid fault detection method (Lei *et al.*, 2014; Yu *et al.*, 2014; Haidong *et al.*, 2020; Liang *et al.*, 2020). The signal processing-based methods demand expertise in mathematics and theoretical representation of fault characteristics and knowledge in estimating the feature frequency of the equipment (Jiao *et al.*, 2020). The physical model-based methods have several drawbacks, such as low accuracy of physical systems of complex machines, need for an in-depth understanding of working principles of the machine, and incapability of the physical models to get updated with real monitoring data. The data-driven fault detection methods such as machine learning overcome many of these issues and deliver remarkable performance. However, machine learning-based methods pose another set of challenges related to feature extraction, optimisation and dimension of data (Jiao *et al.*, 2020).

Induction motor (IM) is a crucial component in several mechanical equipment, and data-driven fault detection of IM is a widely studied area. Various type of data is collected for fault detection such as vibration, sound, pressure, current, chemical analysis and oil analysis data (Gangsar and Tiwari, 2020). A machine learning based fault detection and diagnosis method typically includes data collection, data pre-processing, feature extraction, fault classification and decision making (Alshorman *et al.*, 2020). Numerous classification algorithms such as ANN (Chow *et al.*, 1991; Lashkari *et al.*, 2015), Genetic Algorithm (Nguyen and Lee, 2008; Júnior *et al.*, 2018), Support Vector Machines (Rajeswaran *et al.*, 2018; Gangsar and Tiwari, 2019), Deep Belief Networks (Shao *et al.*, 2017), Sparse autoencoder (Sun *et al.*, 2016), Convolutional Neural Networks (CNN) (Janssens *et al.*, 2018) were implemented for this problem. A detailed review on signal-based fault detection of IM is given in (Gangsar and Tiwari, 2020); the studies based explicitly on artificial intelligence were reviewed in (Alshorman *et al.*, 2020). Current research works in machine fault detection, besides those related to IM, which implemented CNN were reviewed in (Jiao *et al.*, 2020).

2.6.2 Fault detection in construction equipment

The data-driven fault detection methods are widely adopted in construction for structural health monitoring (Jiang and Adeli, 2007; Amezquita-Sanchez and Adeli, 2015; Rafiei and Adeli, 2017; Raphael and Harichandran, 2020). The existing studies in fault detection of construction equipment are limited, and confined to certain specific equipment such as tower crane, excavator and dump truck. Radlov and Ivanov analysed the sequence of failure of mechanical components, which eventually results in tower crane accidents using Fault Tree Analysis (FTA) (Radlov and Ivanov, 2020). The actual implementation of this statistical method seems infeasible due to certain complex requirements, such as correct identification of causal links between individual events in a fault tree and the need for calculating the fault trees corresponds to each operating state of the tower crane. Lin et al. identified the irregular earthmoving operation from image sequences using Faster Region-proposal Convolutional Neural Network (Faster R-CNN) and Long Short Term Memory (LSTM) networks (Lin *et al.*, 2021). They generated line charts equivalent to Crew-balance Charts (CBC) in which abnormal operations were flagged for further corrective actions. The proposed method is applicable only for a limited number of excavator and dump trucks. Besides, the corrective actions can be taken only in the upcoming cycles after evaluating the available results. Implementation of automated construction methods demands detailed investigations on human-machine interaction and fault detection of construction equipment. The current study is the first attempt to develop a robust monitoring system that encompasses activity recognition and early fault detection of automated construction operations.

2.7 DESIGN OF MEASUREMENT SYSTEM

Monitoring and control actions during automated construction are taken based on sensor measurements. In most cases, the locations of sensors are selected based on the generic knowledge of engineers rather than adopting a systematic method (Robert-Nicoud et al., 2005). In the case of structural health monitoring, a tendency towards over-instrumentation is observed (Brownjohn, 2007). Interpretation of data to take appropriate control actions requires the right amount of useful information rather than similar interrelated information in excess. Sometimes, too much unusable data might be an obstruction in interpreting data (Goulet and Smith, 2013). This might even result in an unnecessary increase in the cost of instrumentation as well as interpretation of data. Hence systematic selection of sensor locations that give maximum useful information is of paramount importance. This can be achieved by designing the measurement system. In the design of the measurement system, the type, number and location of sensors and configuration of the test are determined systematically.

The sensor placement is generally a multi-objective optimization problem where the cost of sensor deployment needs to be minimized while maximising the performance of monitoring (Xu *et al.*, 2022). Sensor placement studies are extensively conducted in diverse domains such as structural health monitoring (Mahjoubi *et al.*, 2020; Pachón *et al.*, 2020; Yang *et al.*, 2020); aircraft assembly and design (Haniš and Hromčík, 2011; W. Yang *et al.*, 2019); fault detection (Goyal *et al.*, 2019; Molnar *et al.*, 2020); assessment of indoor air quality (Sharma *et al.*, 2019), and temperature (Arnesano *et al.*, 2016); monitoring of fluid distribution systems (Hu *et al.*, 2021; Xing *et al.*, 2022), and energy systems (Li, 2011; Mobed *et al.*, 2016); irrigation management (do Nascimento *et al.*, 2021); flood detection (Li, 2021) and emergency response planning (Ergen *et al.*, 2015). Numerous optimization methods, machine learning techniques and numerical algorithms were being explored for addressing the sensor placement problem. The studies applied for infrastructure monitoring, and activity recognition relevant to the current research are discussed in the subsequent sections.

2.7.1 Sensor placement for infrastructure monitoring

There are several attempts to arrive at the right locations of sensors for infrastructure monitoring in different scales and for various purposes (Hasni *et al.*, 2018; C. Yang *et al.*, 2019; Yang *et al.*, 2020). Nicoud et al. proposed a multi-model entropy-based methodology for placement of sensors which can be specifically useful in structural system identification scenarios (Robert-Nicoud et al., 2005). In multi-model system identification problems, a measurement system which maximises the separation between candidate models are required. Nicoud et al. used an iterative greedy algorithm to achieve this (Robert-Nicoud et al., 2005). They have taken Shannon's entropy as a criterion for measurement system design. This method arrives at number of sensors and locations which give maximum reduction in entropy or the locations which leads to maximum separation of candidate models. One of the major drawbacks of this method is that the user decides the potential sensor locations. They are expected to have prior domain knowledge in selection of sensors as well as potential locations of measurement. Kripakaran and Smith applied this strategy to instrument bridge and showed that after certain threshold, incorporation of additional sensors will not provide more information (Kripakaran and Smith, 2009). Papadopoulou et al. used a sensor placement methodology based on joint entropy along with influence of modelling error to predict characteristics of wind around buildings (Papadopoulou et al., 2014). However, measurement error incorporated in this study is same for all the sensors used. Goulet and Smith used expected performance for identification and monitoring cost as two parameters to optimize design of measurement system (Goulet and Smith, 2013).

Their results also emphasise how over-instrumentation affects the interpretation of data. Recently, Bertola and Smith proposed a sensor placement methodology which incorporates information gain from static measurements and dynamic measurements for the instrumentation of a bridge (Bertola and Smith, 2019). This method reduces the information redundancy caused by model updating with independent load testing.

2.7.2 Sensor placement for activity recognition

Most of the exiting studies on designing measurement system configuration are developed for infrastructure monitoring. The sensor placement for construction activity monitoring includes challenges such as feasibility of uninterrupted data collection, comfort of the subject in addition to information content. Joshua and Varghese proposed a sensor placement strategy for recognising the activities of bricklayers using decision trees (Joshua and Varghese, 2013). The information gain from each sensor location is estimated through entropy and the order of their selection is determined through decision tree algorithm. The truth table of the movement of the body segments is used for computing entropy, while features of the acceleration measurements were used for activity classification. Therefore, the information content from the features may vary from the initial estimation. Similarly, Kim and Cho used various machine learning classifiers to determine the optimal sensor location (Kim and Cho, 2020). However, they have applied deep learning classifiers for activity recognition based on the selected locations. Consequently, there is inconsistency in the determination of the best sensor locations and their eventual application.

2.8 SUMMARY AND GAPS IN RESEARCH

The current chapter presents a review of the existing studies on Automated Construction Systems, construction equipment activity recognition, machine fault detection methods, and measurement system design. Besides, an overview of the machine learning and deep learning algorithms applied in this study are also described. Existing literature is missing knowledge related to the following aspects, and these knowledge gaps have been bridged in this study:

1. Frameworks to guide the development of integrated monitoring systems for low-rise automated construction
2. Methods to detect early signs of faulty conditions in construction equipment for accident mitigation
3. Methods to identify low-level operation details that may potentially assist in locating the sources of faulty conditions in a low-rise automated construction system
4. Accurate estimation of information content at sensor locations using features that have good potential for discriminating low-level operations of a low-rise automated construction system

CHAPTER 3

METHODOLOGY OF THE RESEARCH

3.1 INTRODUCTION

This research focuses on developing a robust monitoring system for automated construction. The specific research objectives for achieving this aim are the following.

1. Develop an automated operation recognition and fault detection framework which takes into account specific requirements of the automated construction domain, such as:
    1.1. High accuracy of identification
    1.2. High level of details of activities
    1.3. Ability to detect early signs of failure with limited data
2. Design algorithms and methodologies for the efficient implementation of the framework. This includes algorithms for:
    2.1. Sensor placement
    2.2. Operation identification
    2.3. Fault detection
3. Design the experimental setup and evaluate the feasibility of the application of the framework on a full-scale automated construction system.

The research methodology for accomplishing these objectives is described in this chapter. The first part of Section 3.2 is an overview of the research methodology, and the latter part contains the descriptions of each step. The experimental evaluation of the methodology is briefly outlined in Section 3.3, and Section 3.4 concludes the chapter with a summary.

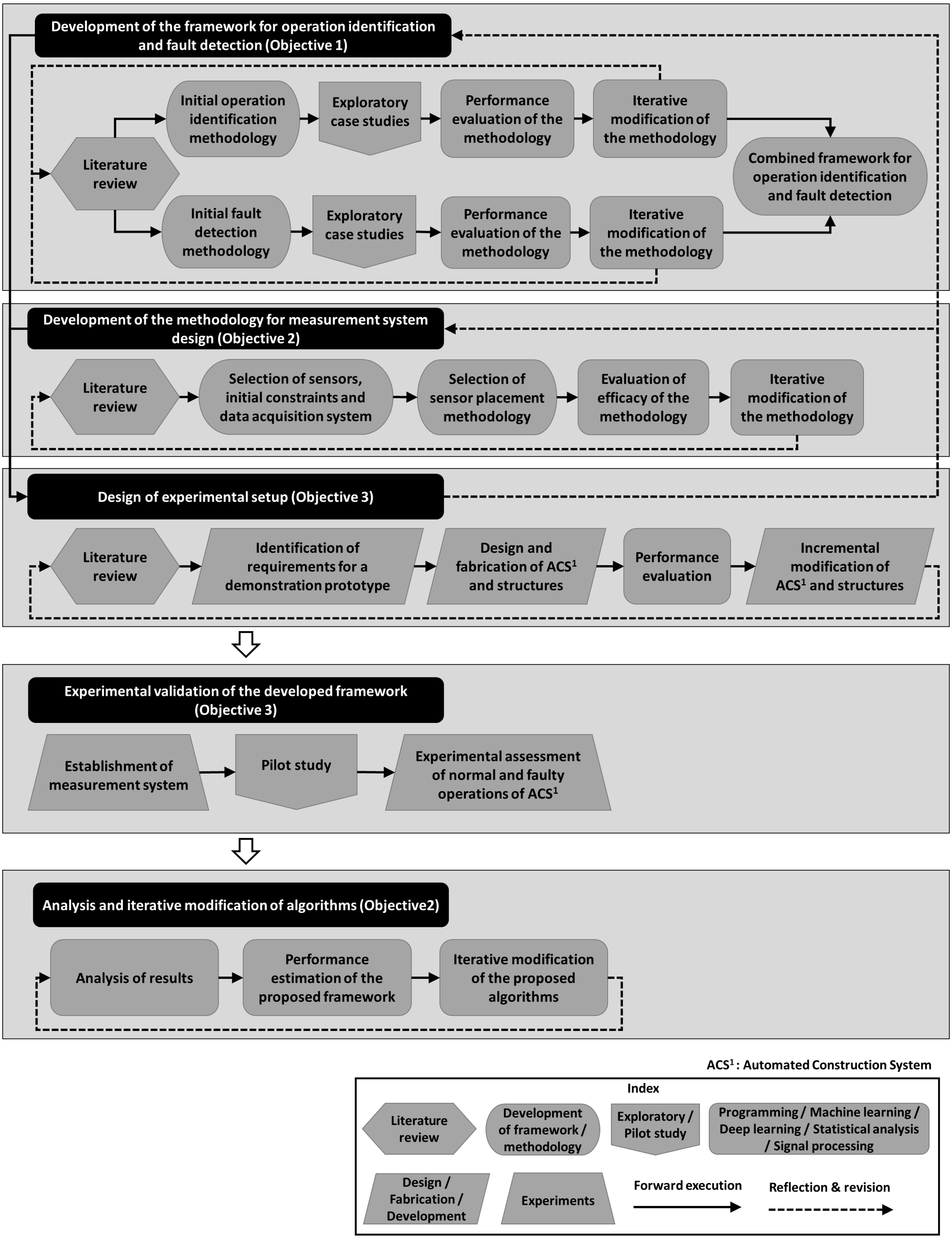


Figure 3.1 Research methodology

3.2 OVERVIEW OF RESEARCH METHODOLOGY

The methodology adopted for the current study is quantitative theory building based on case studies. This methodology involves the development of a conceptual framework followed by empirical verification. The proposed framework was validated through a case study on an Automated Construction System (ACS). The overview of the methodology of this research is presented in Figure 3.1. The research objectives are achieved through the following steps in the methodology: 1) Development of the framework for operation identification and fault detection, 2) Development of the methodology for measurement system design, 3) Design of experimental setup, 4) Experimental validation of the developed framework, and 5) Analysis and iterative modification of algorithms. Each of these steps is described in detail in the following sections.

3.2.1 Methodology steps for achieving objective 1

3.2.1.1 Development of the framework for operation identification and fault detection

Firstly, a methodology is developed for automated operation identification. An initial methodology for identifying normal automated construction operations is developed based on existing literature and the objective of the study. Exploratory case studies were conducted to evaluate the performance of the developed methodology. The exploratory case studies include identifying operations of an Automated Construction System prototype through machine learning. Sensor measurements from the structure or construction equipment are used for machine learning classification. The performance of the proposed methodology is evaluated through various performance measures such as accuracy, precision, recall and F1 score. The identification methodology is iteratively modified to improve its performance. Finally, an identification methodology that delivers high accuracy and a high level of details of construction activity is selected for further study.

Similarly, another methodology is developed for detecting early signs of failure in automated construction. The exploratory studies for developing this methodology include finding faulty conditions in operations of an Automated Construction System prototype. Supervised learning and unsupervised learning methods can be explored for fault detection. Faults in construction equipment often occur in unanticipated circumstances, and data related to such specific conditions are rarely available. Therefore, the developed methodology should be evaluated for its performance with limited data. Finally, a framework for automated construction monitoring is developed by combining the methodologies for operation recognition and fault detection. The framework uses sensor measurements to recognise the normal operations and early signs of faults in automated construction.

3.2.2 Methodology steps for achieving objective 2

3.2.2.1 Development of the methodology for measurement system design

Measurement system design comprises the selection of sensors, data acquisition systems, sensor configuration and related aspects. First, the type of sensors, data collection methods and their constraints are identified from the literature. The sensors are selected based on range, sampling frequency and measurement requirements. The constraints related to measurement locations and the number of sensors are determined based on cost, structural system and construction equipment. The data acquisition system is identified based on types of sensors, communication strategy and data storage systems. Then sensor placement methodology is formulated.

Since this study proposes a data-driven approach for construction monitoring, the results are highly influenced by the quality of the data. Therefore, a scientific approach is adopted for selecting the location of sensors. Initially, a sensor placement methodology suitable for automated construction is selected from the literature. The number, characteristics and locations of sensors are determined through the sensor placement methodology. This methodology is evaluated for its efficacy in delivering relevant information for construction monitoring and selected if it satisfies the research requirements. Otherwise, the existing methodology is iteratively modified to develop a suitable methodology for sensor placement.

3.2.2.2 Analysis and iterative modification of algorithms

The framework for automated construction monitoring consists of methodologies for sensor placement, operation identification, and fault detection. The framework is validated by experimental evaluation on Automated Construction System prototypes. The experiment comprises automated construction in a controlled environment. The experimental results are analysed for identifying operations and faulty conditions using the proposed framework. Then the performance of the framework is estimated. The initial algorithms developed for the methodologies are iteratively modified based on the performance of the framework. This process is repeated until the monitoring framework delivers the best performance.

3.2.3 Methodology steps for achieving objective 3

3.2.3.1 Design of experimental setup

The experimental setup for validating the proposed monitoring framework consists of an Automated Construction System, a structure and a measurement system. Firstly, the existing problems in automated construction are identified through an extensive literature review. Then the requirements for a demonstration prototype of an Automated Construction System are identified. Subsequently, the Automated Construction System is incrementally developed through various laboratory prototypes. The initial prototype is developed for the proof of the concept, followed by the prototypes as per the construction requirements. Each iteration of the design addresses the issues in the previous prototype and gradually introduce new functions. Simultaneously, structural systems are generated by design, fabrication and iterative modification. The structures and construction systems should be compatible with each other. The performance of the system in terms of ease of construction and cycle time is evaluated to determine further modifications.

The purpose of developing this Automated Construction System is to demonstrate the application of the proposed monitoring framework. Besides, the prototypes are developed within the constraints of the budget and time allocated for this research project. Therefore, the Automated Construction System developed in this study may not be optimal or efficient for low-rise automated construction. The development of Automated Construction Systems and structures influence the other steps in the research methodology. The monitoring framework and the measurement configurations are modified based on the changes in the construction systems and structures.

3.2.3.2 Experimental validation of the developed framework

The proposed monitoring framework is validated by experimental evaluation on Automated Construction System prototypes. First, the designed measurement system is established on the Automated Construction System and the structure. Then a pilot study is conducted to verify the measurements and construction operations. After that, actual automated construction experiments are conducted. The experiments consist of normal automated construction operations and faulty operations under controlled conditions. The proposed framework is validated for recognising operations and detecting faults in operations. This step is followed by the analysis of the experimental results and iterative modification of algorithms (described in Section 3.2.2.2).

3.3 EXPERIMENTAL EVALUATION

The theoretical framework and methodologies proposed in this study are validated on an Automated Construction System prototype for low rise building construction. This system follows an automated top-down construction method. Acceleration measurements from the structure are used for identifying operations and faulty conditions. The experiments are conducted in a controlled laboratory condition under the supervision of trained experts. It involves normal operation cycles and potential faulty conditions in the automated construction. The experiments which cover normal operations involve two complete cycles of top-down construction. The experiments for faulty conditions are designed to capture the early signs of failure during construction within the safety norms.

First, the sensor placement methodology is validated, and the optimal sensor configuration is determined. Then the methodologies for operation identification and fault detection are validated. These methodologies are combined after optimising their algorithms to generate the framework for automated construction monitoring. The performance of the proposed framework and methodologies is benchmarked with that of corresponding conventional approaches. The algorithms for operation recognition and fault detection are iteratively modified to obtain the desired performance. The generalizability of the proposed framework is assessed through its application on a benchmark dataset.

3.4 SUMMARY

The overall methodology of this research is described in this chapter. The research methodology starts with the development of the monitoring framework. The next step is the development of methodology for measurement system design. This step is followed by the design and development of Automated Construction Systems and structures. Then the developed framework is experimentally validated. The final step is the analysis of the experimental results and iterative modification of algorithms. The monitoring framework is validated on an Automated Construction System prototype for low-rise buildings.

CHAPTER 4

THEORETICAL FRAMEWORK AND ALGORITHMS

4.1 INTRODUCTION

The current chapter presents the theoretical framework and algorithms developed in this study. Firstly, the framework for automated construction monitoring is presented in Section 4.2. Subsequently, Section 4.3 outlines the algorithms for training and testing the monitoring framework. Then the methodology for measurement system design and sensor placement is described in Section 4.4. This is followed by a description of the methodology for operation identification in Section 4.5. Finally, the contents of this chapter are summarised in Section 4.6.

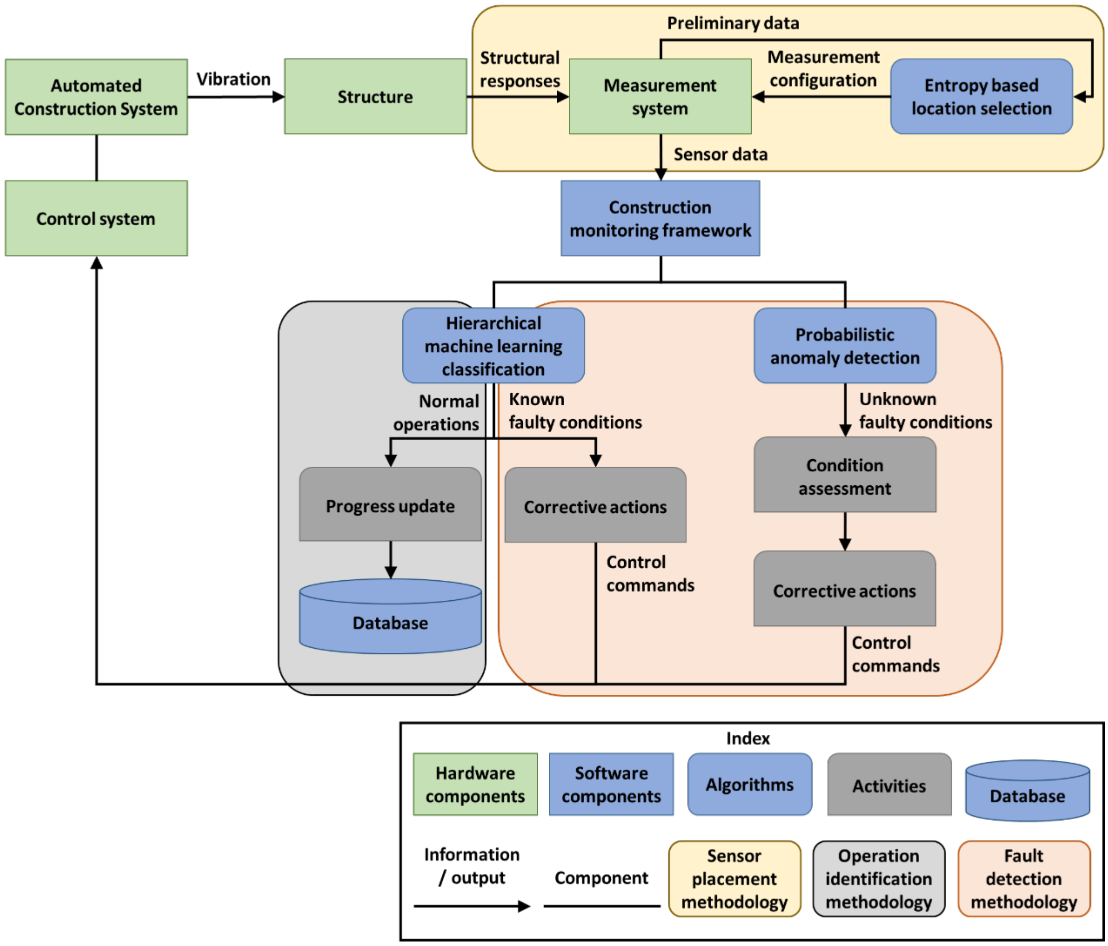


Figure 4.1 HUS-ML framework for automated construction monitoring

4.2 HUS-ML FRAMEWORK FOR AUTOMATED CONSTRUCTION MONITORING

Activity recognition and fault detection are critical tasks in automated construction monitoring. Existing studies on construction equipment monitoring have focused mainly on activity recognition and tracking. Fault detection has not been given much attention. This is a more challenging task because many unforeseen conditions might arise during the actual operation of the construction equipment. This study proposes a novel activity recognition and fault detection framework called HUS-ML (Hybrid Unsupervised and Supervised Machine Learning). The HUS-ML framework consists of three main conceptual components: 1) sensor placement methodology, 2) operation identification methodology, and 3) fault detection methodology. The interaction of the HUS-ML components and flow of information for automated construction monitoring are illustrated in in Figure 4.1.

Operations of an Automated Construction System induce vibrations on the structure. The responses from the structure are measured using a measurement system. The configuration of the measurement system is determined through the sensor placement methodology based on preliminary measurements. After measurement system design, the measured sensor data is supplied to the HUS-ML monitoring framework. A hierarchical arrangement of the identification problems in this framework extracts a high level of operation details. Supervised learning and unsupervised learning ensure accurate identification of normal operations and faulty condition. First, identification is attempted through supervised learning using training data of previous operations. Then an anomaly detection algorithm is applied to spot any unseen faulty conditions. If the identified operation is normal, the progress of construction is updated in the database. If the operation is identified as faulty during supervised learning (known faulty operations), corrective actions can be taken after completing hierarchical identification. If the faulty conditions are detected through unsupervised learning (unforeseen faulty operations), further investigation is needed before corrective actions. The corrective actions are executed through the control commands sent to the control system of the Automated Construction System.

The methodology for operation identification and fault detection by the HUS-ML framework is presented in Figure 4.2. Each step of the methodology is described in detail as given below.

1. **Controlled experiments:** Controlled experiments consist of automated construction operations in normal and faulty conditions. Faulty operations are performed in controlled conditions to capture early signs of failure.

2. **Collection of sensor data:** The sensors are deployed at critical locations on the structure or construction equipment. The sensor measurements during operations are collected through data acquisition systems.

3. **Data pre-processing:** The measured data is visualised to check anomalies and the correctness of the information. The ground truth labels are generated for operations. The labelled datasets are subjected to further cleaning, feature extraction, feature scaling, and splitting.

4. **Algorithm selection and tuning:** The best classification algorithm and its parameters are selected for supervised learning through exploration and testing. The best features for fault detection are also determined.

5. **HUS-ML Training phase:** Automated construction activities are divided into different identification levels based on their hierarchical relationships. The topmost identification level contains abstract classes, and the lower levels include the subcategories with more details. The machine learning model for an activity recognition problem is termed a classifier; the model for a fault detection problem is termed a detector. The machine learning algorithms selected at step 4 are assigned to respective activity recognition problems. The best features that have been selected are used for fault detection. The classifiers and detectors at every identification level are trained with datasets of that particular level. More details are provided in section 4.3.1.

6. **Optimisation of activity recognition and fault detection models:** The initial performance of classifiers/ detectors on the training dataset is assessed. Hyperparameters of the models are tuned to ensure the best performance for identification problems. N-fold cross-validation is performed to avoid overfitting, where N is the number of folds.

7. **Actual automated construction:** The equipment is used for the actual construction on site, and data is collected from the sensors. In this study, an Automated Construction System prototype is operated in laboratory conditions for the testing and demonstration of the methodology. The construction activities used for testing in this study include trained normal operations, trained faulty operations, and untrained faulty operations.

8. **HUS-ML Testing phase:** Unseen data points (test data) generated during the actual construction are used to identify operations and faults. The algorithm navigates each data point through various identification levels starting from the topmost level. The data point is redirected at each identification level to a classifier or detector based on the results from the previous identification level. A detailed description of the testing phase is given in section 4.3.2.

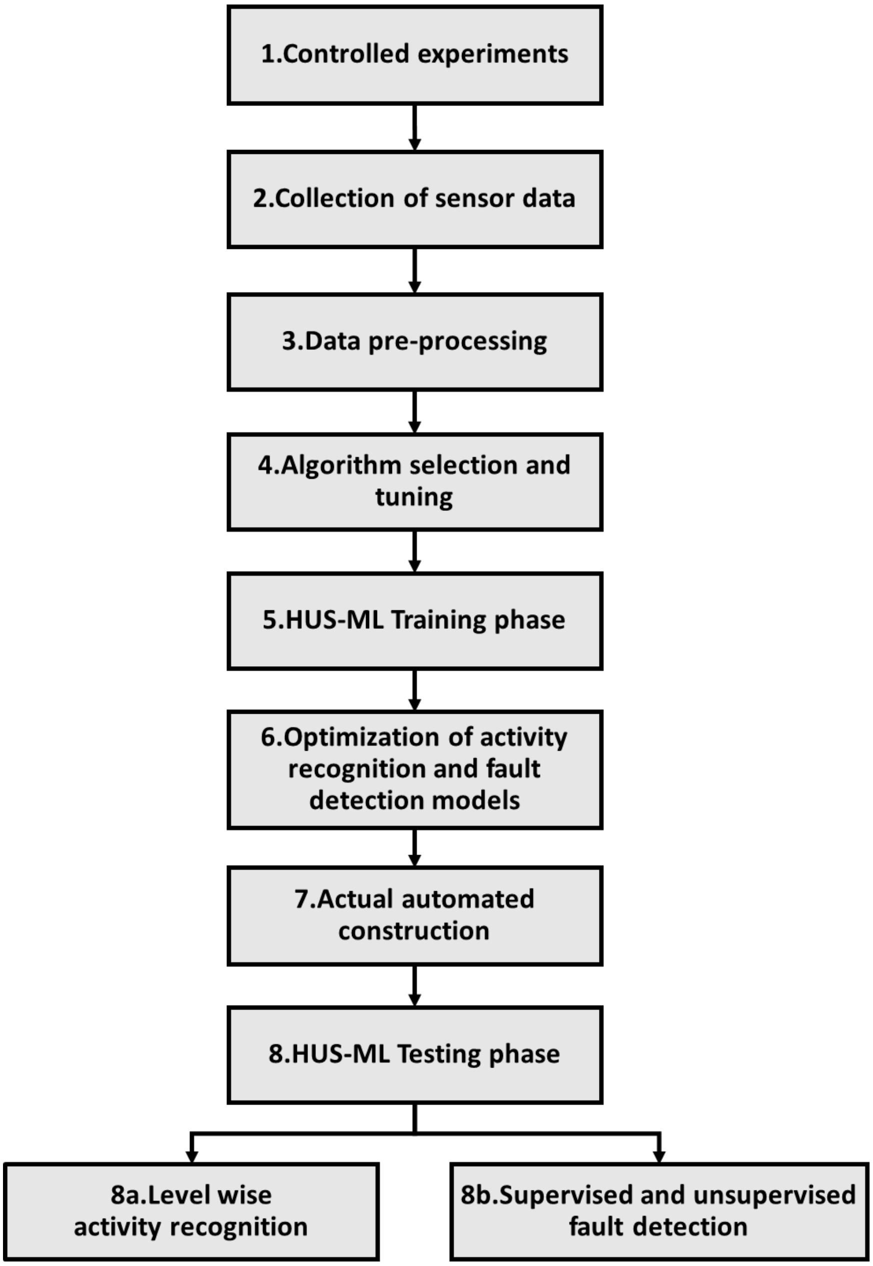


Figure 4.2 Overview of operation identification and fault detection by HUS-ML

4.3 HUS-ML: ALGORITHMS FOR OPERATION IDENTIFICATION AND FAULT DETECTION

4.3.1 Training phase

The training phase of the HUS-ML framework is illustrated in Figure 4.3. The activity recognition and fault detection are performed at multiple identification levels, where information gained from a level is fed into the next level for more elaborate and refined identification. At each identification level, the data is subjected to supervised learning followed by unsupervised learning. During supervised learning, the construction activities or faulty operations are identified using the training dataset. The identified activity is then further analysed using an anomaly detection algorithm to spot any unseen faulty conditions. Hence, the HUS-ML framework has a two-stage fault detection strategy to identify known faulty operations and unforeseen faulty operations.

The HUS-ML training starts with a hierarchical decomposition of the construction activities into various identification levels. After activity decomposition, machine learning models are assigned for each identification problem in the hierarchy. Two studies were conducted in the pre-design phase of HUS-ML training, each for supervised learning and unsupervised learning. These studies were performed for algorithm selection and tuning. Then, training data collected from controlled experiments or generated by simulation will be supplied as input to the first identification level. Once all the HUS-ML models are trained at the first identification level, the training is continued for the next identification level. This process is continued till HUS-ML training at all identification levels is completed.

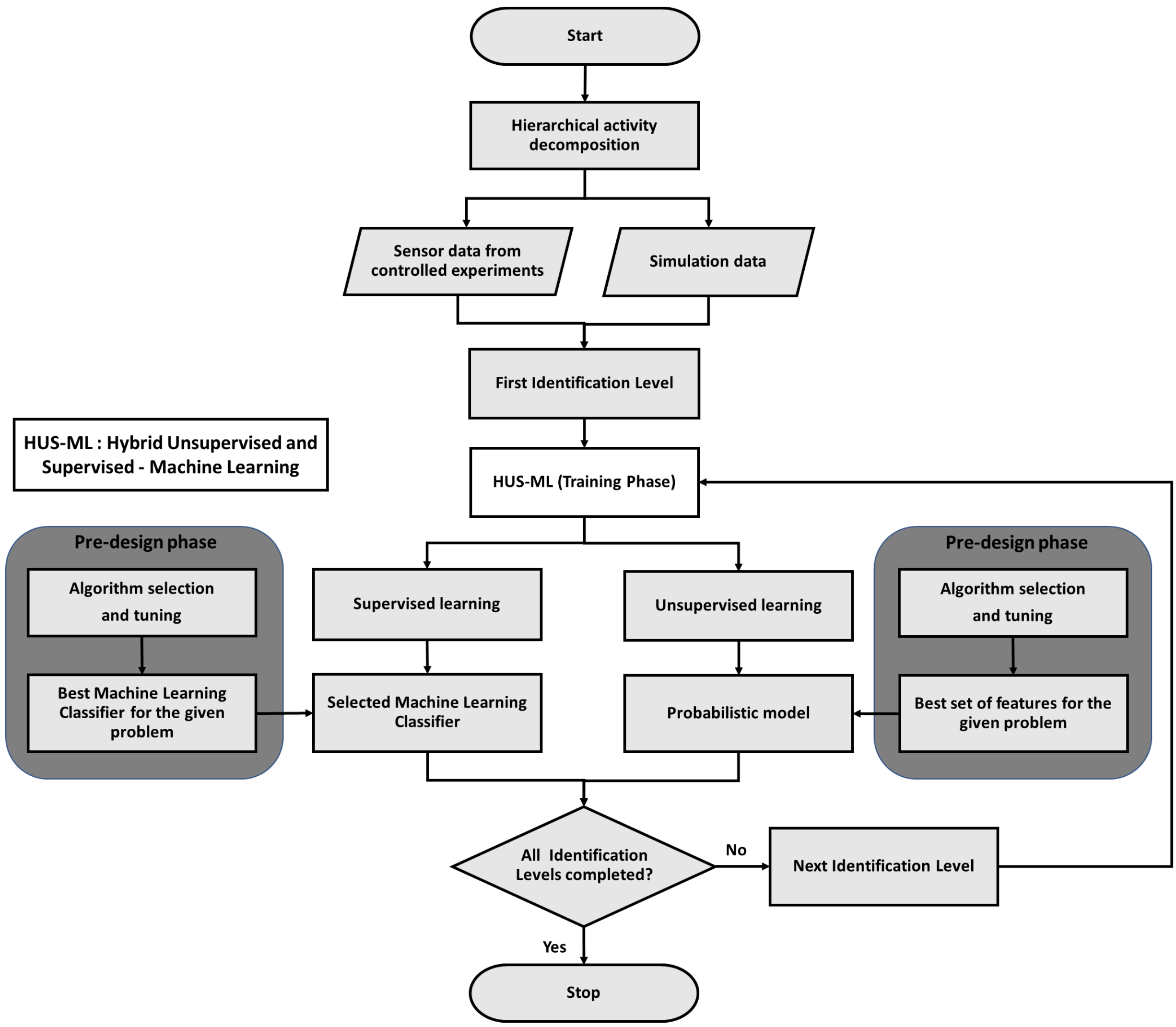


Figure 4.3 HUS-ML flowchart for training stage

The HUS-ML training at each identification level consists of supervised learning and unsupervised learning. Supervised learning models are trained to recognise actual operations or faulty operations from the given classes. Unsupervised learning generates probabilistic models by fitting the distribution of the input data. A threshold on the probability is used to identify any potential faulty operations. This procedure is explained in more detail below.

The first step for identifying unseen faulty operations is to fit a Gaussian model to the distribution of the correct operation. The unlabelled data set for training, *{d(1), ..., d(m)}* contains only correct operations, where *m* is the number of training instances.

The Gaussian distribution for each feature *di* has to be estimated for the training dataset as given in Equation (4.1).

$$p(d;\mu,\sigma^2)=\frac{1}{\sqrt{2\,\pi\,\sigma^2}}e^{-\frac{(d-\mu)^2}{2\,\sigma^2}} \tag{4.1}$$

The parameters μ and $\boldsymbol{\sigma^2}$ denote mean and variance, respectively. These parameters can be computed by Equations (4.2) and (4.3) to fit data in the i^{th} dimension.

$$\mu_i=\frac{1}{m}\sum_{j=1}^{m} d_i^{(j)} \tag{4.2}$$

$$\sigma_i^2=\frac{1}{m}\sum_{j=1}^{m}\left(d_i^{(j)}-\mu_i\right)^2 \tag{4.3}$$

After estimating the Gaussian parameters, the probability of each data point in the fitted distribution can be calculated. The data points with very low probability tend to be faulty operations. A threshold is selected based on a cross-validation dataset to determine the faulty operations. Let $\{(d_{cv}^{(1)},l_{cv}^{(1)}),\dots,(d_{cv}^{(m_{cv})},l_{cv}^{(m_{cv})})\}$ be the labelled cross-validation dataset where $(d_{cv}^{(i)},l_{cv}^{(i)})$ denotes the i^{th} data point and corresponding label, and m_{cv} is the number of instances in the cross-validation dataset. Faulty operations were labelled as one, and normal operations were labelled as zero. The probability of each data point in the cross-validation dataset $p(d_{cv}^{(i)})$ is computed. If $p(d_{cv}^{(i)})<T$, then it is considered as a faulty operation, where T is the selected threshold. The probability vector for the cross-validation dataset $p(d_{cv}^{(1)}),\dots,p(d_{cv}^{(m_{cv})})$ is compared with the ground truth label set $l_{cv}^{(1)},\dots,l_{cv}^{(m_{cv})}$ and the F1 score is computed by Equation (4.4). The F1 score shows the fault detection performance with the given threshold T. Different values of T were applied on the cross-validation dataset, and F1

scores were computed to determine the best value of *T*. The selected threshold *T* is used to determine the faulty operations in future predictions.

$$F1\,score = \frac{2\ x\ Precision\ x\ Recall}{Precision + Recall} \tag{4.4}$$

Here a simple probabilistic model is presented for fault detection. In theory, more complex models could be used; however, there are several challenges. The identification of anomalies in high dimensional space is one of the major challenges in anomaly detection. Deep anomaly detection methods were explored for solving this issue (Pang *et al.*, 2021).

4.3.2 Testing phase

Figure 4.4 shows the flowchart of the testing phase, which is typically performed during the actual construction. This stage might involve normal operations and faulty operations that the framework trained to identify and unseen faulty operations that the framework has never seen before. The input data is redirected at each identification level to an appropriate model based on the prediction results from the previous level. Therefore, more information about a specific operation is available after the prediction at each identification level.

The input data is subjected to supervised learning prediction followed by unsupervised learning prediction at each identification level. If the operation is identified as faulty during supervised learning prediction, the algorithm will proceed to further identification levels to collect more information. Appropriate control or corrective actions can be taken readily since detailed information is available after completing all identification levels.

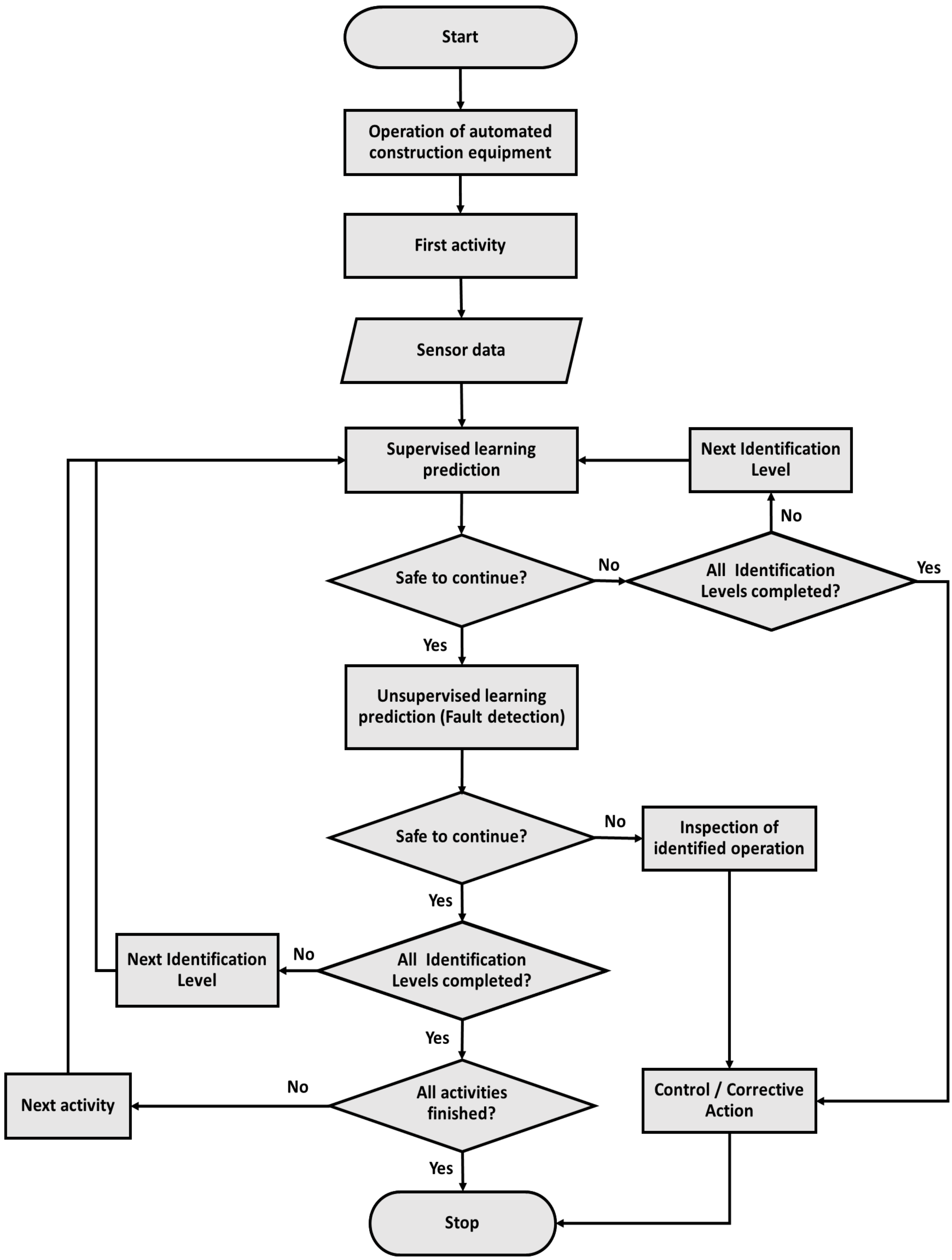


Figure 4.4 HUS-ML flowchart for prediction at the operation stage

If the operation is identified as normal at a specific identification level, the data is subjected to unsupervised learning to detect potential unknown faulty conditions. If the operation is still identified as normal at this stage, we can proceed to the subsequent identification levels and operations. Otherwise, we need to inspect the ongoing operations to identify the faulty condition. Corrective actions need to be taken based on the inspection result to rectify the faults. Thus, the HUS-ML framework detects both known and unknown faulty operations through a rigorous two-stage fault detection.

4.4 METHODOLOGY FOR SENSOR PLACEMENT

The current study adopts a data-driven method for automated construction monitoring; the quality of information collected highly influences the findings of the study. Therefore, a scientific approach is followed to design the measurement system for acquiring relevant and good quality information. The measurement system design contains three stages: 1) determining the details regarding data acquisition, 2) identifying initial sensor locations, and 3) systematic sensor placement.

Firstly, the type of measurement or data for construction monitoring is determined. The data can be in the form of visuals, audios or kinematic measurements based on the construction equipment we intend to monitor. Once the data type is decided, the initial constraints related to the measurement system are identified. The initial constraints include the practical aspects such as the overall budget of the research project, availability, cost and ease of installing the sensors and data acquisition system (Robert-Nicoud *et al.*, 2005).

Secondly, the initial locations of sensors are selected from which a scientific method is adopted to arrive at the optimal location. The initial locations are determined based on domain knowledge and heuristics. The locations for construction monitoring are decided by considering the structural behaviour and characteristics of construction equipment. The criteria for selection include a) locations where measurement vary with changes in construction operations, b) locations that do not interrupt construction operations, c) locations where the entire duration of the construction can be captured, and d) locations that give maximum observable measurements during construction (high signal to noise ratio).

Finally, the initial sensor locations are systematically evaluated for their information content to determine the sensor configuration. The information content is estimated by Shannon's entropy function proposed by Shannon and Weaver (Shannon, 1948; Shannon and Weaver, 1964). The entropy, E, is computed as given in Equation (4.5).

$$E = \sum_{j=1}^{S} -P(v_j)\ log_2 P(v_j) \qquad (4.5)$$

where $P(v_j)$ is the probability of an instance in the j^{th} interval of the distribution of the variable, v. The current study proposes a methodology for optimal sensor placement based on this entropy function. It is described in the following sections.

The objective of sensor placement in the current study is to monitor automated construction operations. Therefore, the measurements from the sensor locations should contain enough information to identify construction operations and potential faulty conditions. Data-driven machine learning techniques were adopted to detect operations and faults from sensor measurements automatically. Hence, the proposed sensor placement methodology uses features extracted from the raw data as variables for computing the entropy. The concept of sensor placement based on Shannon's entropy was initially proposed by Robert-Nicoud *et al.*(Robert-Nicoud *et al.*, 2005). The current methodology departs from the existing study in terms of variables and the objective of measurement system design. The previous studies used this approach to separate model classes for falsification, whereas the current study focuses on instance classification. While the existing studies use the distribution of raw data for location selection, the current study incorporates the features for identification. Figure 4.5 shows the sensor placement method proposed in this study, and each step is described as follows.

1. A list of all the subsets of instances that need to be separated, termed 'Subset_List', is generated. The initial Subset_List contains only one element, the set of all the instances for identification. After each iteration, this list contains the subsets which were not separated by the information from the selected variable.

2. Two lists of variables are created. The first list contains all the variables for construction monitoring, termed as the 'Vars_List'. The second list, 'Sel_Vars', is created to move the selected variables from Vars_List during each iteration. The Sel_Vars is empty before the first iteration. The variables include the features of measured data from each sensor location. The name of each variable contains the name of the selected feature and the sensor location. For example, the variable name 'IQR_AM4' means the feature Interquartile range extracted from accelerometer data installed at location number four.

3. Repeat step 7 to step 9 for each subset in Subset_List.

4. Create a histogram of each variable in the Vars_List. The width of the histogram is computed as the average range of the variable for operation classes. The probability of an interval is the number of instances in an interval divided by the total number of instances in the subset.

5. The entropy of variables in the Vars_List is computed from the probability values.

6. The variable with maximum entropy is selected for separating the instances in a subset. The selected variable is moved from Vars_List to Sel_Vars.

7. Divide each subset into children subsets based on the histogram distribution of the selected variable. Update the Subset_List by replacing the current subset with its children subsets.

8. Remove the subsets which contain one instance or multiple instances of the same operation class from Subset_List.

9. Repeat steps 4 to 7 until all the subsets are completely separated, or the Vars_List is empty.

10. Identify optimal locations of sensors and features from the selected variables in Sel_Vars.

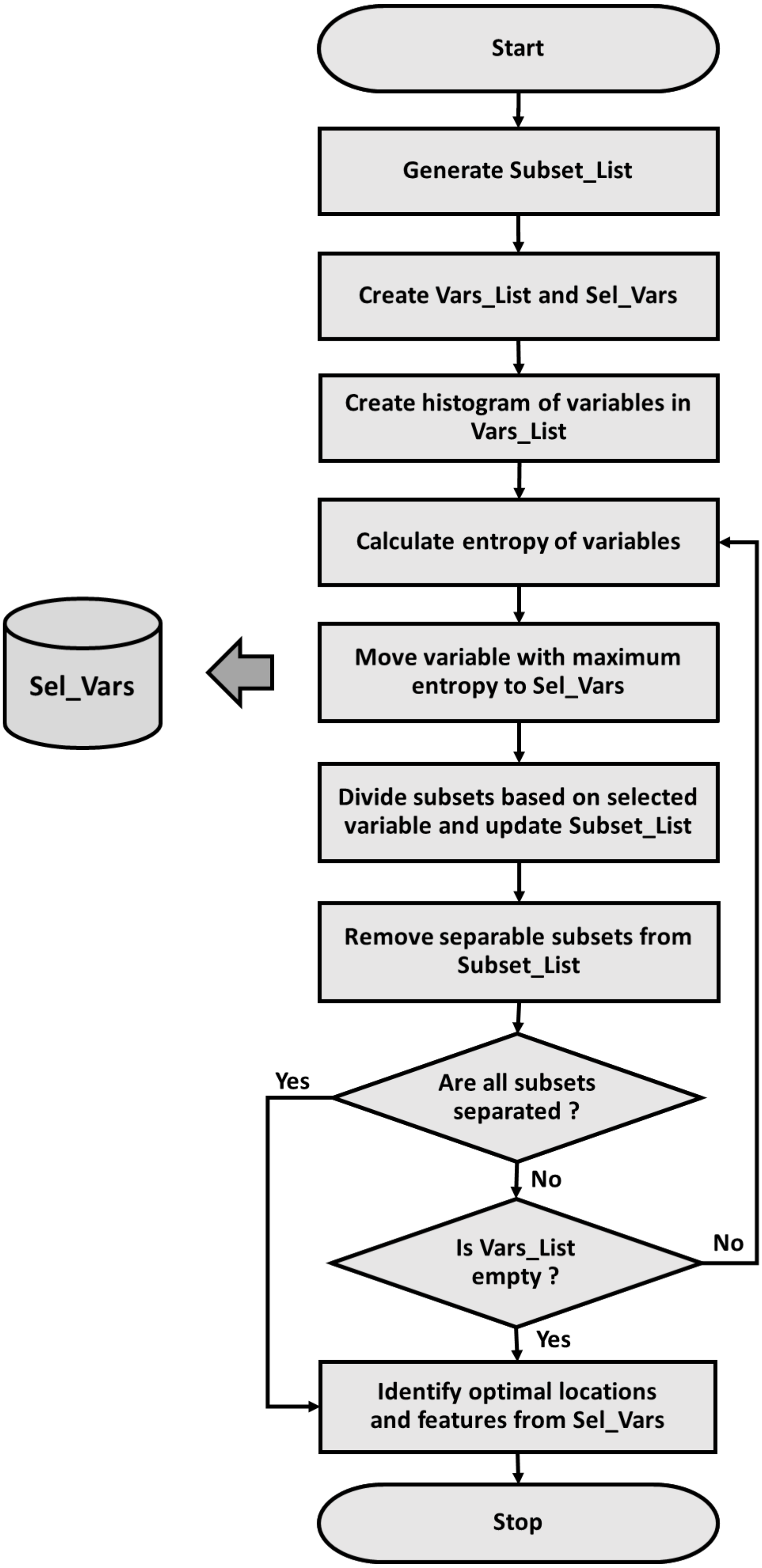


Figure 4.5 Sensor placement methodology

The optimal locations of sensors can be determined through this method. Apart from these, additional locations could be included in the measurement configuration for redundancy. The variables with maximum information content may also indicate better features in the feature space. Therefore, the proposed methodology could also be used for feature selection.

4.5 METHODOLOGY FOR OPERATION IDENTIFICATION

The current research evaluates two different problem formulations for operation recognition: 1) the conventional approach adopted in previous studies (Figure 4.6), and 2) the hierarchical method proposed in the current study (Figure 4.7). The operations are classified into finer subclasses from the top level to the bottom level. Classification level 1 consists of the operation states of the construction equipment, namely, idle and operations. The idle state indicates that the equipment is turned on, but no operations are being performed. The data generated in this state is primarily due to ambient vibrations. Classification level 2 further divides the operations into major classes. Classification level 3 contains the subclasses of operations based on operation sequence or machine configuration. All operation subclasses are divided at classification level 4 based on the stage of construction. Both methodologies are evaluated for their ability to identify operations at four classification levels. All the operation classes are supplied as a flat list to the conventional approach. However, the identification is separated into four levels to compare its performance with the hierarchical identification methodology.

4.5.1 The conventional approach for operation identification

The conventional approach for operation identification comprises a flat list of classes (Figure 4.6). Each classification level contains one identification task (classification problem) and a machine learning classifier assigned to solve this problem. A machine learning classifier is defined as a predictive model trained to solve a classification problem in this context. The machine learning model at classification level N is termed Classifier N. The formulation of the identification problem in the conventional approach is shown in Figure 4.6. The grey box represents the classification level N, and the blue box represents the machine learning classifier at this level. The operations classified by Classifier N is also shown in blue boxes.

Most previous studies have adopted this problem formulation for operation identification (Akhavian and Behzadan, 2015; Rashid and Louis, 2019; Shi *et al.*, 2020). It does not use any activity relationships or information from the previous classification level. The classifiers at each level are optimised independently to ensure the best performance. As the classification level increases, the complexity of the learning task also increases. The topmost classification level contains a few operation classes, while lower levels contain numerous classes based on the construction tasks. The initial operation identification was performed using the conventional approach to verify its suitability for identifying a large number of classes.

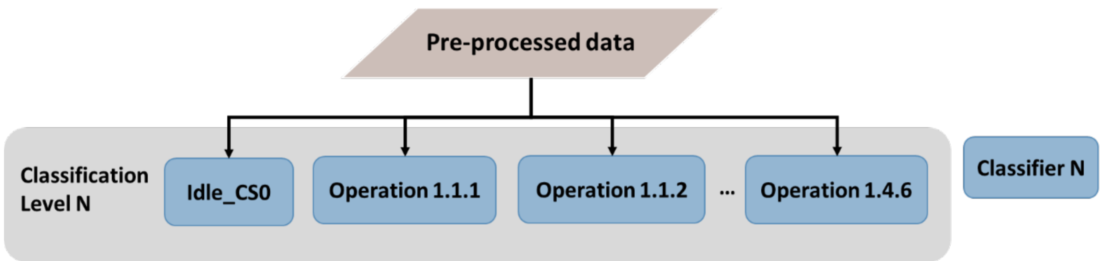


Figure 4.6 Conventional approach for operation identification

4.5.2 The hierarchical operation identification methodology

The hierarchical methodology proposed in this study formulates the identification problem based on the hierarchical relationship between construction operations (Figure

4.7). The identification task is divided into various classification levels. Each classification level uses information from the previous level to simplify the identification task. There can be more than one identification task per classification level. Accordingly, there is a hierarchy of machine learning classifiers, each assigned to solve an identification task. The machine learning classifiers are numbered systematically as 'Classifier L.N' where L represents the classification level, and N represents the number of the classifier at classification level L. Each machine learning classifier classifies similar operations at a particular level.

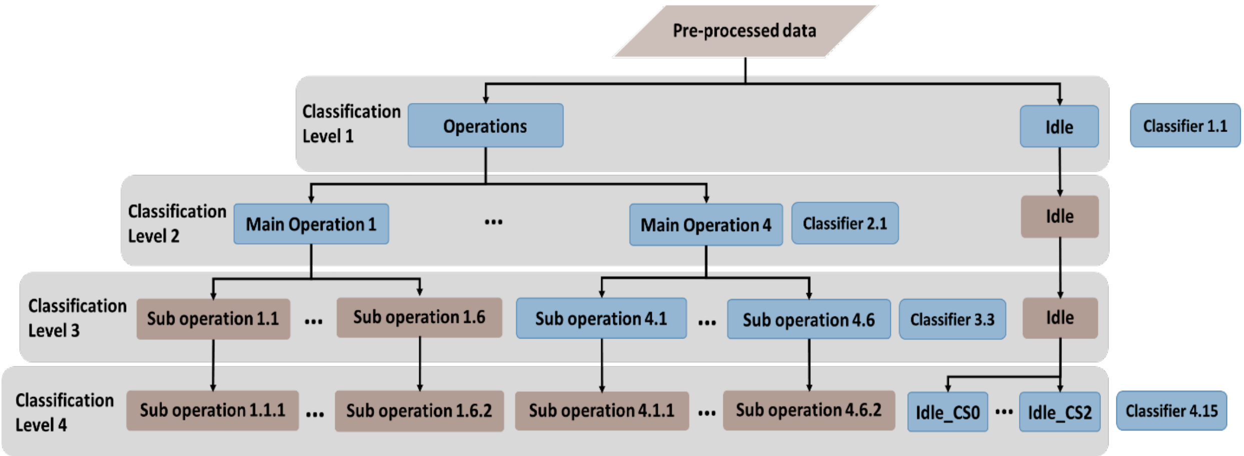


Figure 4.7 Hierarchical methodology for operation identification

The formulation of the identification problem in the hierarchical methodology is presented in Figure 4.7. The direction of the black arrow shows the logical flow of information across classification levels. The data points are redirected at each classification level to an appropriate classifier based on the prediction at the previous level. Therefore, predictions at each classification level refine the information from the previous levels. Each classification level contains multiple classifiers; only one classifier is presented in this figure for clarity. The performance of the hierarchical methodology in operation identification is benchmarked with that of the conventional approach. The hierarchical operation recognition methodology is adopted for developing an automated monitoring framework in this research.

4.6 SUMMARY

The methodologies, algorithms, and theoretical framework developed to identify operations and faulty conditions in automated construction are presented in this chapter. Firstly, the HUS-ML framework for operation recognition and fault detection is presented. This framework uses a combination of supervised and unsupervised learning strategies for identifying operations and faulty conditions. The algorithms for the training and testing of this framework are discussed after that. Subsequently, the measurement system design is briefly introduced, followed by the sensor placement methodology. Shannon's entropy function is used for finding the optimal sensor locations and features for activity classification. The methodologies for operation identification are introduced in the end. This includes the conventional approach and a newly proposed hierarchical methodology. The hierarchical methodology identifies construction operations based on their hierarchical relationships.

CHAPTER 5

EXPERIMENTAL EVALUATION

5.1 INTRODUCTION

This chapter describes the experimental evaluation of the developed framework on an Automated Construction System (ACS). The automated construction method adopted in this study is briefly introduced in Section 5.2. A detailed description of the experimental setup is provided in Section 5.3. Then, automated construction experiments were presented in Section 5.4. After that, data collection and pre-processing were described in Section 5.5 and Section 5.6. Finally, the chapter is summarised in Section 5.7.

5.2 AUTOMATED TOP-DOWN CONSTRUCTION

A vast majority of Automated Construction Systems (ACS) are mainly designed for high-rise building construction (Hamada *et al.*, 1998; Gassel, 2005; Bock and Linner, 2016b). System Skanska, J-up system and NCC Komplett are the existing low-rise Automated Construction Systems. The NCC Komplett adopts a construction environment similar to a manufacturing factory. However, System Skanska and J-up system follow the 'ground factory - building push-up' method (Bock and Linner, 2016b). The author of this study has developed an automated top-down construction system for low-rise buildings with others (Raphael *et al.*, 2016; Harichandran *et al.*, 2020b). The ACS has been developed incrementally through multiple laboratory prototypes with varying complexity in three years. More details on the development of the ACS prototypes and their performance are described in 9.4APPENDIX B APPENDIX B and APPENDIX C The monitoring framework proposed in this study is validated through an experimental setup that comprises the ACS prototype three, hereafter referred to as the Automated Construction System prototype or the ACS prototype.

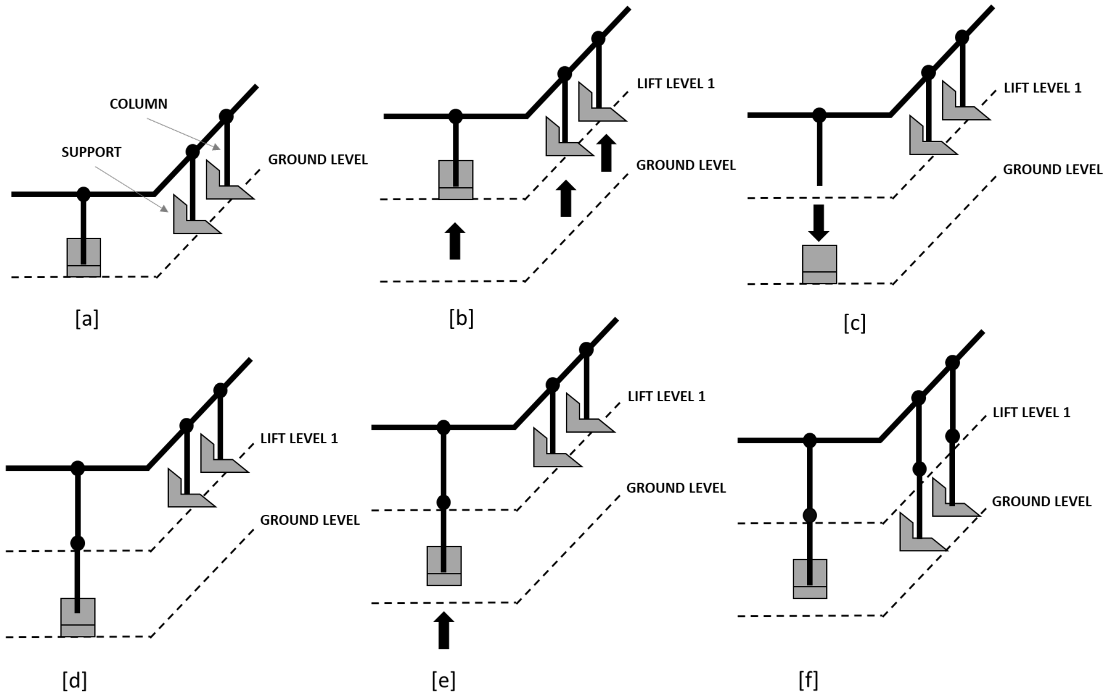


Figure 5.1 Automated top-down construction operations

The Automated Construction System prototype in this study follows an automated top-down construction method (Harichandran *et al.*, 2020b). The construction scheme is similar to the 'ground factory - building push-up' method (Bock and Linner, 2016b). However, the current method is used to build the structural frame of low-rise buildings. It is a modular construction method and uses light construction equipment. The main operation and controls unit of the construction system is located at the ground level. The structure is constructed module by module and lifted progressively by the Automated Construction System. The construction starts from the topmost floor, followed by the lower floors. The structural frame is supported by the platforms or supports at each location of the column. The automated top-down construction method can be categorised into two based on the configuration of the structure and the ACS. More details regarding these construction categories are described in APPENDIX A

The experiments in this study are conducted by the automated top-down construction category I, hereafter referred to as the automated top-down construction.

Figure 5.1 is a simplified illustration of automated top-down construction operations. The structural frame is illustrated in black, and the supports of the Automated Construction System are in grey. Each column consists of several modules assembled at each lift level of construction. All operations starting from a particular lift level belong to the same Construction Stage (CS). Several construction stages (CS0, CS1, …) constitute the construction of one floor of a structural frame. The stability of the structure during top-down construction is ensured by its specially designed configuration and additional supports. The major operations in one cycle of automated top-down construction are as given below (Figure 5.1).

- [a] Assembling beam modules and the first set of column modules of the topmost floor and supporting the assembled structure at the ground level
- [b] Lifting all the supports of the Automated Construction System gradually at once to move the partially completed structure to lift level 1 (Coordinated Lifting)
- [c] Lowering one of the supports while the structure is carried by the remaining supports (Lowering Support)
- [d] Connecting column module to the unsupported column (Connection of Column Module)
- [e] Lifting the support until the load from the structure is transferred (Lifting Support)
- [f] Repeating steps [b] to [e] for the remaining columns

After completing all operations at CS1, the subsequent construction cycle for CS2 starts. The current example shows the automated top-down construction with a structure containing redundant supports as in the present study. For more information on other automated top-down construction schemes for low rise building construction, refer APPENDIX A

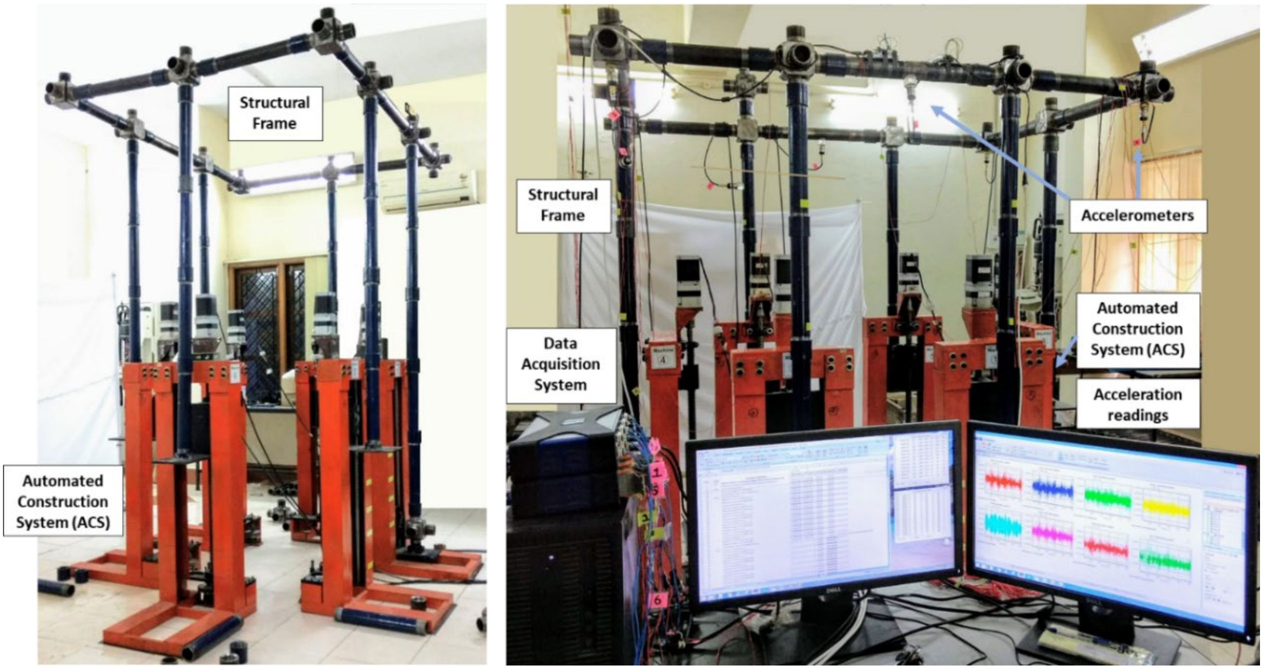


Figure 5.2 An overview of the experimental setup

5.3 THE SETUP FOR AUTOMATED CONSTRUCTION EXPERIMENTS

The experimental setup is developed to validate the automated construction monitoring framework proposed in this study. The scope of the research includes automatically identifying the operations and detecting the faulty conditions during the construction of a low-rise structural frame through an Automated Construction System (ACS). The experimental setup comprises three components: 1) ACS, 2) structural system, and 3) measurement system or data acquisition system. An overview of the experimental setup is illustrated in Figure 5.2. The measurement system is designed and deployed to collect sensor measurements from the structure during the automated construction. The measured data is used for automatically identifying the operations and detecting the faulty conditions through the intelligent algorithms of the monitoring framework. Each component of the experimental setup is described in the subsequent sections.

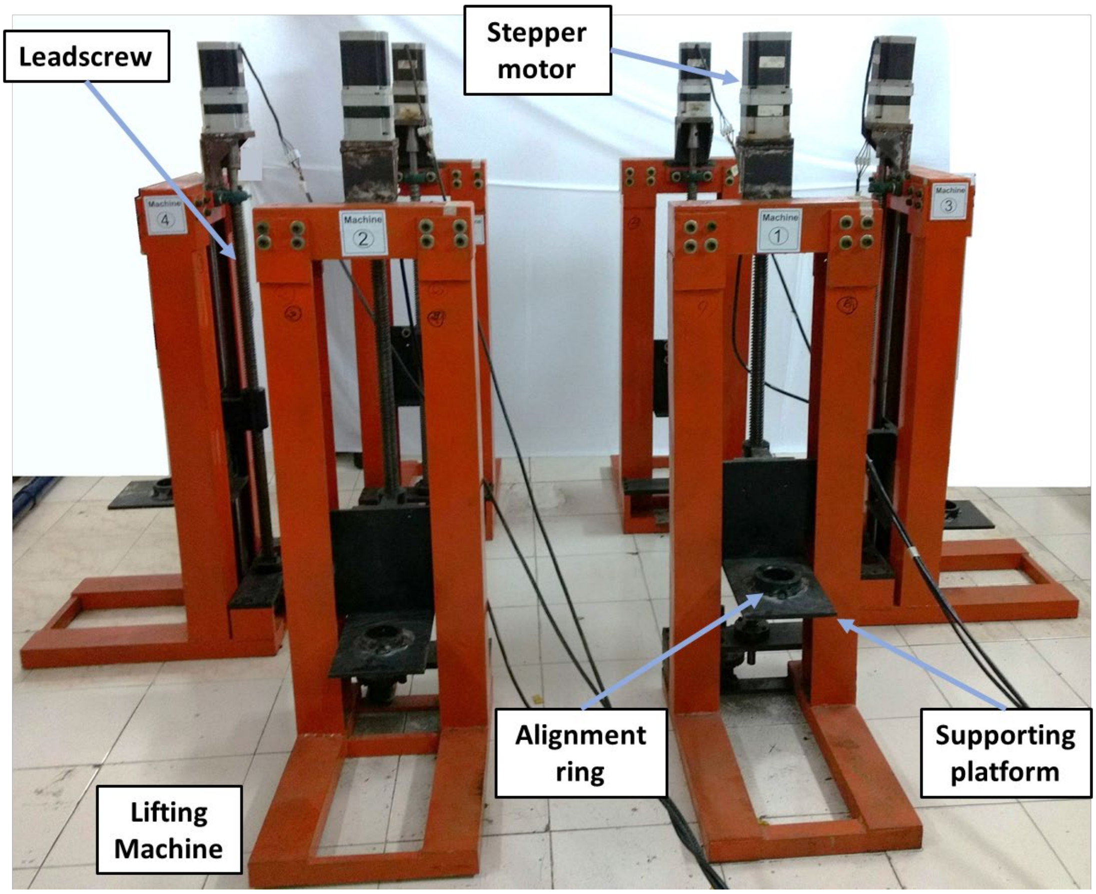


Figure 5.3 The Automated Construction System (ACS) with six lifting machines

5.3.1 The Automated Construction System

The Automated Construction System (ACS) in the experimental setup comprises six lifting machines, each having a two-ton lifting capacity (Figure 5.3). The construction system is controlled by programmable Arduino microcontrollers and operated at an average lifting speed of 0.35 m/min. All construction operations except connection are automated. The lifting machines can be operated individually and simultaneously. Each lifting machine has a supporting platform to support one column of the structural frame. An alignment ring is provided on the supporting platform to ensure the correct alignment of column modules. The supporting platforms are lifted or lowered through a leadscrew connected to a high torque hybrid stepper motor (manufactured by Bholanath Precision Engineering Pvt. Ltd., model no.: BH86 SH 118 - 6004 PL).

An adequate number of lifting machines can be arranged at the ground level based on the size and configuration of the structure. Therefore, this construction system favours a high level of flexibility for the building design. The current study is conducted on a room-scale structural system. Therefore, the lifting machines in the ACS are closely placed to fit the structural configuration. The machines are arranged to face their lifting platforms outward to build the structural frame around the ACS (Figure 5.4).

Figure 5.4 Partially constructed structural frame on the Automated Construction System (before instrumentation)

5.3.2 The structural system

The modular configuration of the structural system in this study is developed based on the concept of Robot-Oriented Design (ROD) to facilitate automated construction (Bock and Linner, 2015, 2016b). The structural frame comprises several small modules made of standard steel tube sections. The tube sections have a 50 mm nominal bore and 4.5 mm thickness. The plan and elevation of the structural frame are illustrated in Figure

5.5 and Figure 5.6. All modules carry eternal threading at their ends. Every module is connected by a single coupler or by a combination of couplers and universal joints, depending on the location of the module. Couplers are standard steel sockets with a 50 mm nominal bore and 65 mm length. The universal connectors are custom-made steel joints made from the same materials used for the structural modules. The universal connectors facilitate connections in all axial directions.

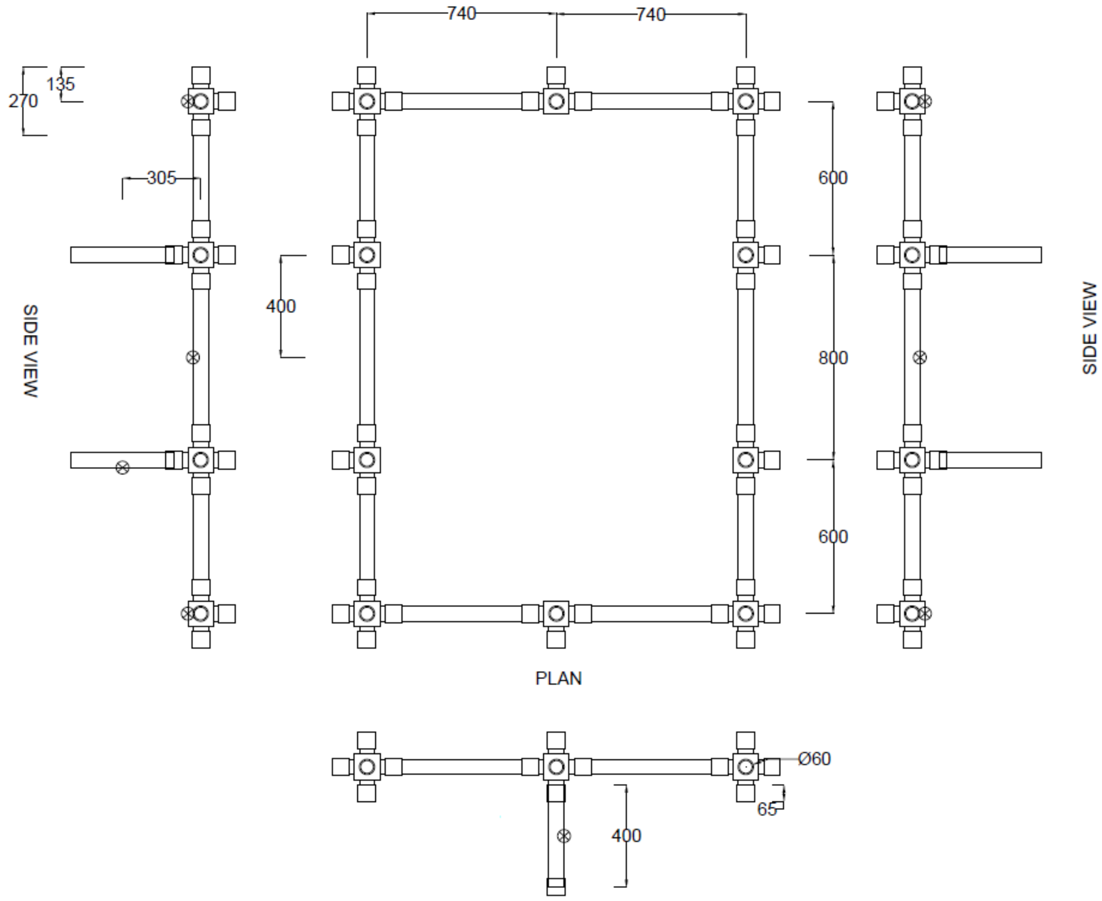


Figure 5.5 Plan of the structural frame. All dimensions are in mm.

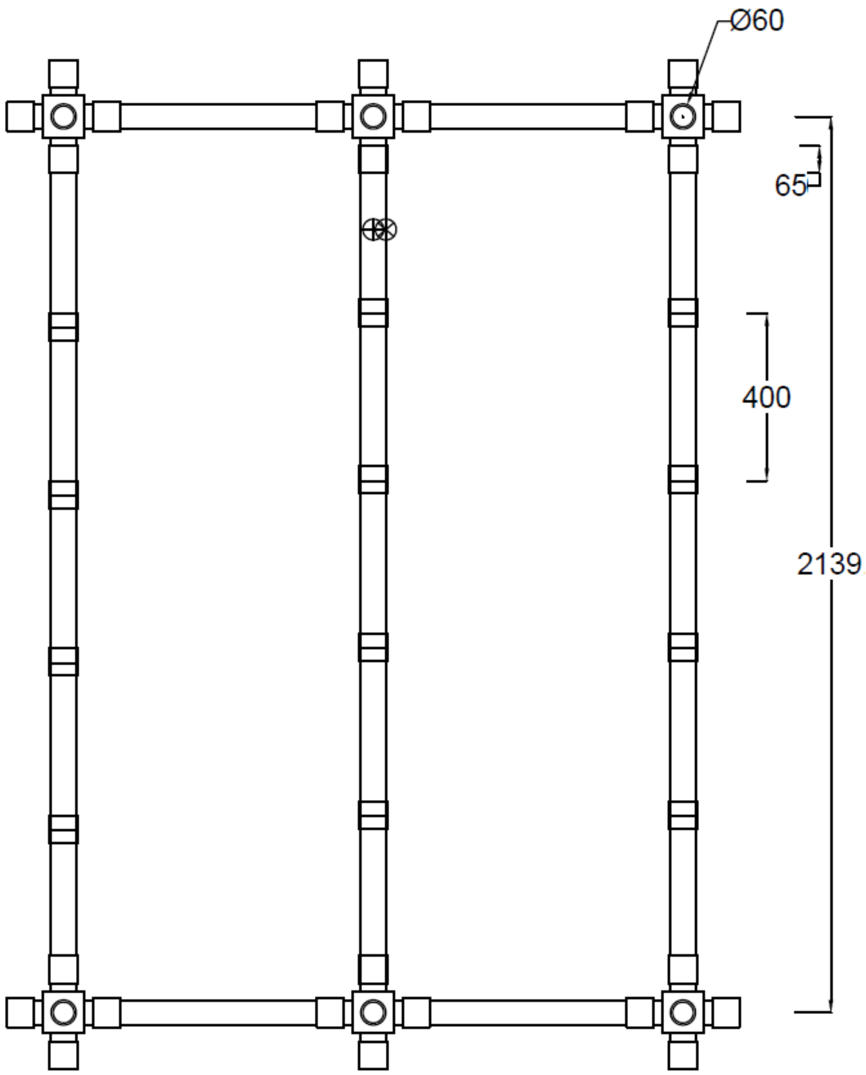


Figure 5.6 Elevation of the structural frame. All dimensions are in mm.

5.3.3 The measurement system

Measurement system design is the fundamental stage for any experimental study. The quality and reliability of the data collection depend on the efficiency of the measurement system. The initial measurement configuration is designed based on domain knowledge and heuristics. After that, optimal sensor locations are determined by the sensor placement methodology described in the earlier chapter.

A vibration-based method is found to be suitable for identifying Automated Construction System operations based on an extensive review of equipment activity recognition methods. All operations induce vibrations in the structure which have signature patterns associated with them. After careful consideration of the configuration and operation sequence of the Automated Construction System prototype, the accelerometer is selected for data collection. Figure 5.7 shows the sensor locations on the structural frame. The initial sensor locations are selected based on practical aspects of ongoing construction; and feasibility for 1) uninterrupted data collection, 2) coverage for the complete operation cycle, and 3) maximum measurable vibrations (high signal to noise ratio). Accelerometers are numbers as AM1, AM2, …, AM8.

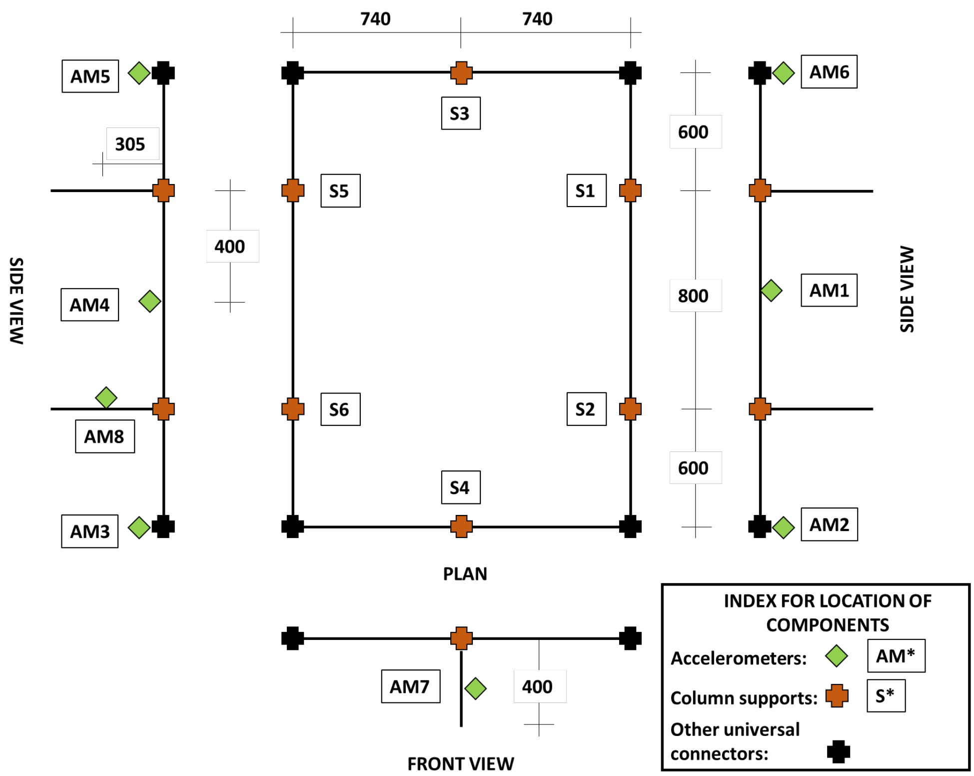


Figure 5.7 Sensor locations on the structural frame (All dimensions are in mm)

5.3.4 Significance and adequacy of the experimental setup

The ACS prototype developed for this study can construct the structural frame of a full-scale three-storey building. However, the scope of this research is limited to a room-scale structural frame to evaluate the HUS-ML framework in a controlled environment. The J-up system developed by Sekisui House, Ltd., Japan, for low-rise building construction is similar to the ACS discussed in this study (Bock and Linner, 2016b). This is a simple and cost-effective system for constructing residential buildings up to three floors high. The lifting operations in the J-up system are automated through hydraulic jacks. However, the building components connected manually. Therefore, the ACS prototype developed for this study adequately represents the existing low-rise automated construction methods.

The experimental setup was designed to simulate an actual construction situation as much as possible in the laboratory. In an actual construction site, the equipment might be different, and the types of faults might be different. However, the monitoring framework can still be applied. This generalizability of the monitoring framework is demonstrated using a completely different application in section 8.4.

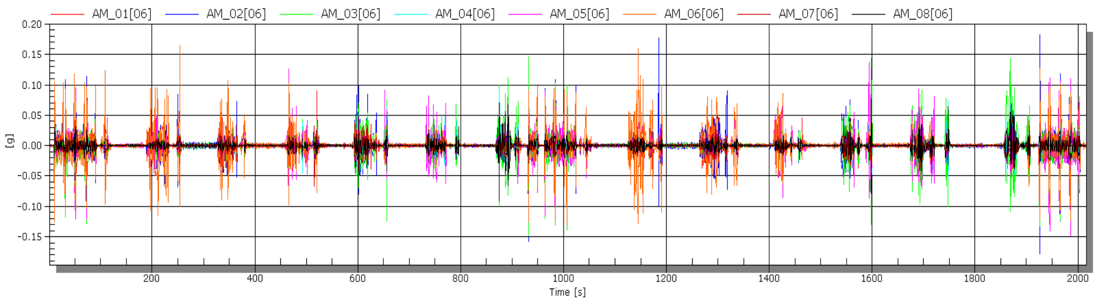


Figure 5.8 Screenshot of the accelerometer data for two cycles of automated top-down construction

5.4 AUTOMATED CONSTRUCTION EXPERIMENTS

The automated construction experiments were conducted in a controlled laboratory condition. The experiments were planned to capture normal operation cycles and potential faulty conditions in an automated top-down construction. Any type of change in the part or component of the machinery that prevents it from performing its intended function satisfactorily is termed as a machine fault (Jayaswal *et al.*, 2008). Faults in the current study is defined as the conditions in the ACS that causes to deviate from its normal operations. The experiments which cover normal operations involve two complete cycles of top-down construction. Each of these experiments spans around 30 - 45 minutes and is repeated six times. More than 19 million measurements were collected for normal operations. Figure 5.8 shows raw acceleration measurements from one set of experiments.

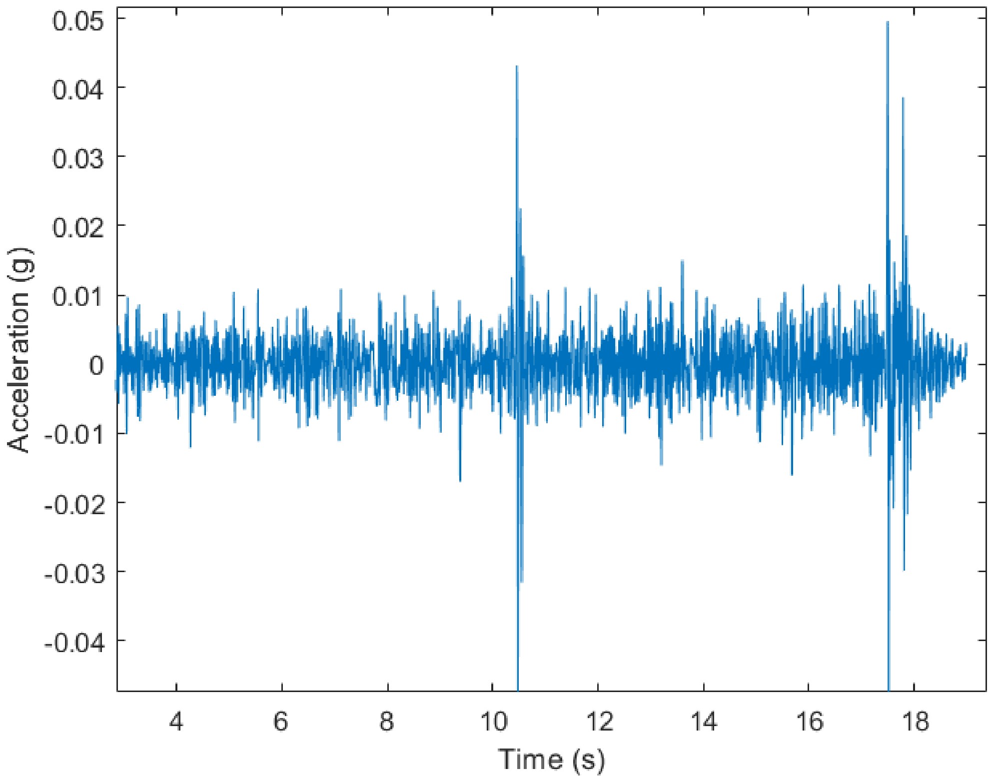


Figure 5.9 Acceleration measurements from AM1 corresponds to asynchronous coordinated lifting

Coordinated lifting is a critical operation in automated top-down construction. Asynchronous coordinated lifting or uneven load distribution during Coordinated lifting may result in severe accidents. Therefore, the experiments for collecting faulty operation data involves capturing the early signs of two of these faulty conditions. The experiments were performed in a controlled condition under the supervision of trained experts. Each of these experiments was repeated 12 – 13 times, and more than 3 million measurements were collected for faulty operations. The objective of these experiments was to capture early signs of failure during construction. Hence, the experiment duration was planned to collect the required data to indicate deviation from the normal condition; within the safety norms.

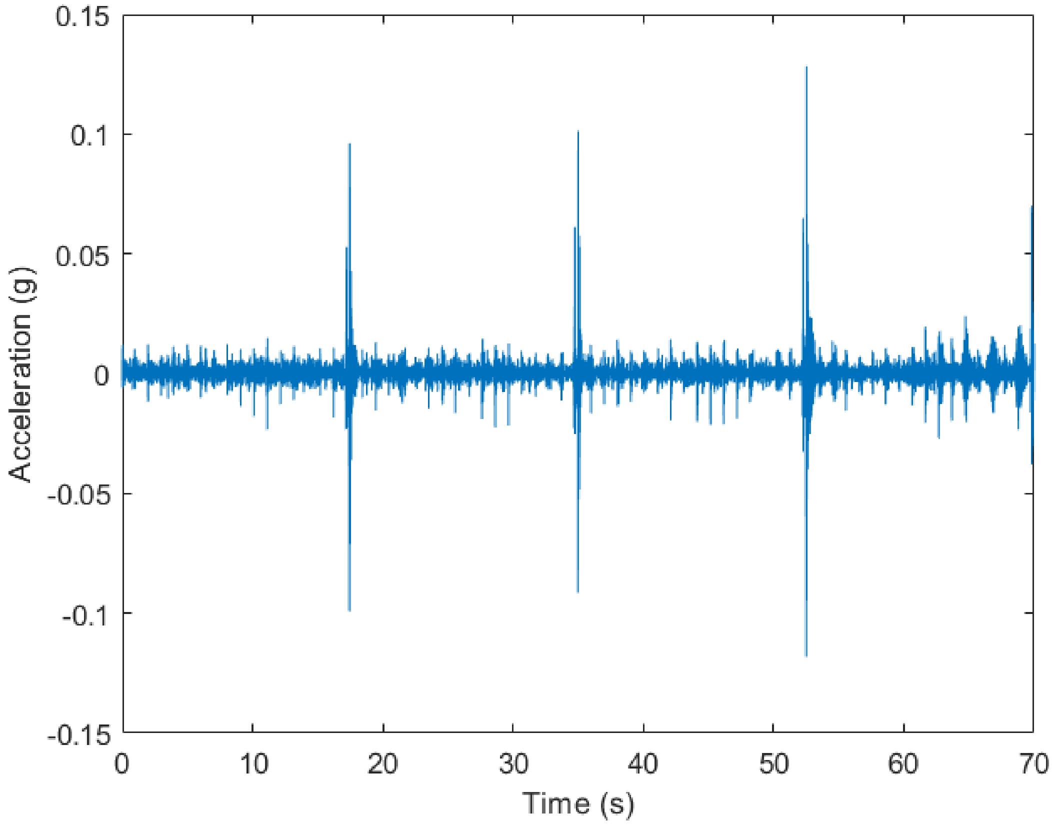


Figure 5.10 Acceleration measurements from AM1 corresponds to coordinated lifting with a non-contact support

The asynchronous coordinated lifting condition is introduced by programming one support to move faster than the other supports. Ideally, all supports should rise at the same speed during Coordinated lifting. Suppose one of the lifting machines is out of synchronisation with the other due to mechanical faults. This may not be easily distinguishable at the early stages of operations. But, if allowed to continue, it will result in the overturning of the entire structural system in a matter of seconds. Hence, vibration patterns from the structure at the beginning stage of Coordinated lifting are captured in a controlled manner (Figure 5.9).

One of the causes for uneven load distribution is the noncontact of the support and the structure after the lifting operation. This condition is introduced by a partial lifting of one of the supports so that it does not result in load transfer. Then acceleration measurements correspond to one cycle of Coordinated lifting is collected under controlled conditions. Figure 5.10 shows acceleration measurements during coordinated lifting with non-contact support. The pattern of measurements during this faulty condition is highly similar to that of normal Coordinated lifting.

This study explores whether these early signs of failure can be detected effectively to avoid potential accidents. The conditions that lead to failure are carefully introduced during experiments to collect data corresponding to these conditions. These data are required to develop the machine learning model that predicts the deviations from normal behaviour. It is not possible and not necessary to simulate all types of failure conditions to create this model. Besides, creating the complete failure of the system and potentially endangering people involved are neither necessary nor economically viable. Most of the failure conditions are unprecedented. Hence, the current study also explores a novel anomaly detection-based method to account for unforeseen faulty conditions. An unseen and completely different experimental dataset of faulty conditions is introduced during the testing phase to evaluate the efficacy of the HUS-ML framework.

5.5 DATA COLLECTION

The control unit of the Automated Construction System and data acquisition system are located at the ground level. HBM universal measuring amplifier (model: QuantumX MX840B, Number of channels: 8) is used for acquiring accelerometer data with timestamps. Based on previous studies on construction equipment activity recognition (Akhavian and Behzadan, 2014, 2015; Hyunsoo Kim *et al.*, 2018) and Nyquist criterion

(Lyons *et al.*, 2005), the sampling frequency for data collection is set to 200Hz. This sampling rate ensured the capturing of minute vibrations during machine operations without creating excessive data. The data was collected using CATMAN data acquisition software (HBM, 2020) and later imported to Microsoft Excel (XLSX format) and MATLAB (mat format) files for further analysis. Separate time tracking excel sheets are used for recording timestamps of each operation during the experiments. This data is compared with the timestamps from the data acquisition system to extract signals corresponding to each operation accurately. The automated construction experiments for normal operations involve two complete construction stages (CS), as shown in Figure 5.11. A trained operator controls the Automated Construction System while two unskilled labours carry out the connection of the modules. All other operations and data collection are automated.

Each operation in the automated top-down construction has a pattern of acceleration associated with it. The vibration of the machine and the structure during the operation cycle is captured in the acceleration data. Intuitively, all the automated operations should have similar patterns irrespective of the repetition of the experiment or operating cycle. However, the structure changes with every operation either due to the addition of modules or changes in supporting conditions during lifting and lowering. Hence the vibration patterns corresponding to these operations will show variations (Figure 5.11). This makes the identification problem far more complex than it appears. For example, the acceleration patterns of operations at support number 1 for two construction stages (CS1 and CS2) can be studied in Figure 5.11. The operations, lowering of support and lifting of support are completely automated. However, the patterns in the data for these operations do not appear to be similar in the corresponding regions of CS1 and CS2. This dissimilarity in patterns can be observed in other operations as well. In the case of the connection of modules, the pattern of measurement and duration of the operation is likely to change in every repetition of the experiment and operation cycle. Even though these highly depend on the labourer involved in the operation, a general trend can be observed. Among the operations, some of them have similar patterns. As the classification becomes finer, the complexity of identification increases.

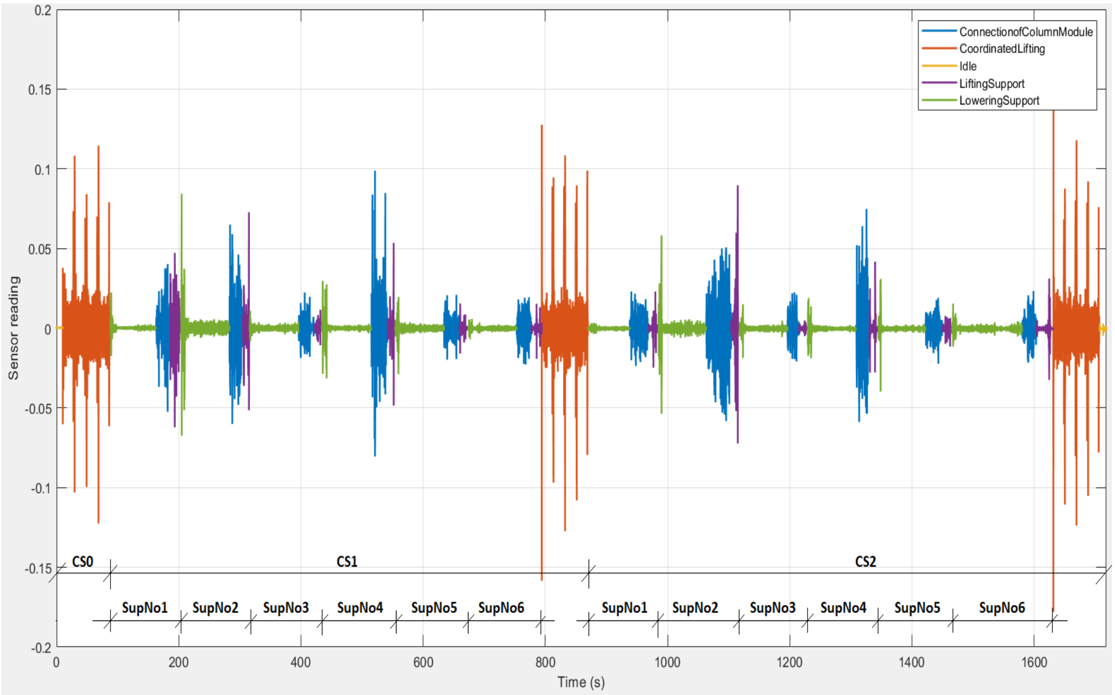


Figure 5.11 Acceleration measurements (unit: g) from AM2 in the normal operations experiment involving two complete construction stages (CS). Significant operations and states are coloured according to classification level 2.

5.6 DATA PRE-PROCESSING

The raw acceleration data were visualised through CATMAN to check for spurious patterns or missing data. After preliminary data cleansing, the time series data were compared with the Excel logbook to generate ground truth labels. The labelled datasets were then imported to MATLAB for further pre-processing.

The raw data have to be represented in the form of features to enable better learning. Five time-domain features and five frequency-domain features were extracted from the raw data. Totally 80 features (10 features x 8 accelerometers) were extracted. The time domain features are mean, variance, root mean square error, interquartile range (IQR), and peak values of the acceleration data. The frequency domain features include three of the first main frequencies from Fast Fourier Transform (FFT), period of the signal, and energy of the signal from autocorrelation. The data segmentation is avoided to test the ability of the features to represent the entire construction activity. Instead of selecting a subset of features, the entire feature space is utilised for supervised learning. Preliminary studies using the current computer system (Processor: Intel(R) Core (TM) i7-8700T CPU @ 2.40 GHz, installed memory (RAM): 16GB) showed that this feature space would not result in high computational cost and time. Hence the whole feature space is preserved for the potential improvement in activity identification. However, only selected features were used for fault detection. The datasets were split into 70:30 for training and testing based on the lowest subcategory of the activity labels.

5.7 SUMMARY

The proposed framework and methodologies were evaluated on an automated construction system for low rise buildings. The construction system follows an automated top-down approach where the topmost building components were constructed first and lifted sequentially. The experiments consist of normal operation cycles of automated top-down construction and potential faulty operations in a controlled laboratory setup. Acceleration measurements from the critical locations on the structure are collected during construction. The raw data is subjected to pre-processing for further analysis. The timestamps of the measured data are compared with the digital logbook to create ground truth labels of operations. Time domain and frequency domain features were extracted for machine learning classification. Analysis of the measured data and validation of the proposed methodologies were described in the following chapters.

CHAPTER 6

ANALYSIS AND RESULTS: MEASUREMENT SYSTEM DESIGN

6.1 INTRODUCTION

The configuration of the measurement system influences automated monitoring of construction. Several studies have been conducted on various aspects of construction monitoring such as data collection, sensor types, algorithms, and equipment to improve performance (Ahn *et al.*, 2015; Akhavian and Behzadan, 2015; Golovina *et al.*, 2019; Rashid and Louis, 2020). However, systematic methods to determine the measurement configuration are limited (Joshua and Varghese, 2013; Soman *et al.*, 2015). Most of the time, the engineers decide the measurement locations based on convenience and heuristics (Goulet, 2012). This may result in over instrumentation and causes additional costs for data collection and computational efforts for cleaning, analysis and interpretation of measured data.

The current study proposes a sensor placement methodology to scientifically determine the measurement configuration based on information content. The evaluation of sensor placement methodology on the Automated Construction System prototype is described in this chapter. The measurement system design for automated construction monitoring is described in Section 6.2. Implementation of the proposed sensor placement methodology for automated construction is presented in Section 6.3. Section 6.4 contains the results and discussion of the study, and Section 6.5 concludes the chapter with a summary of the findings.

6.2 MEASUREMENT SYSTEM DESIGN FOR AUTOMATED CONSTRUCTION MONITORING

Kinematic measurements from the structure or construction equipment are selected to identify automated construction operations based on an extensive literature review (Section 2.5). All operations induce vibrations in the structure which have signature patterns associated with them. After careful consideration of the configuration and operation sequence of the Automated Construction System prototype, the accelerometer is selected for data collection. The initial senor configuration is determined based on heuristics and measurement constraints such as a) locations that give maximum vibration during construction, b) locations where normal operations will not get affected, c) locations where the entire duration of the construction can be captured. The initial locations of sensors on the structure are displayed in Figure 6.1. Eight monoaxial piezoelectric accelerometers (1000 mv/g sensitivity and -5g to +5g measurement range) are fixed on the topmost beam-column assembly of the structure. They are numbered as AM_01 to AM_08. AM_07 and AM_08 are positioned at the mid-height of the topmost column modules, parallel to ground level and perpendicular to each other. AM_01 to AM_06 are placed on different locations on the bottom surface of the beam assembly perpendicular to ground level. The optimal locations of sensors are determined through the sensor placement methodology developed in this study.

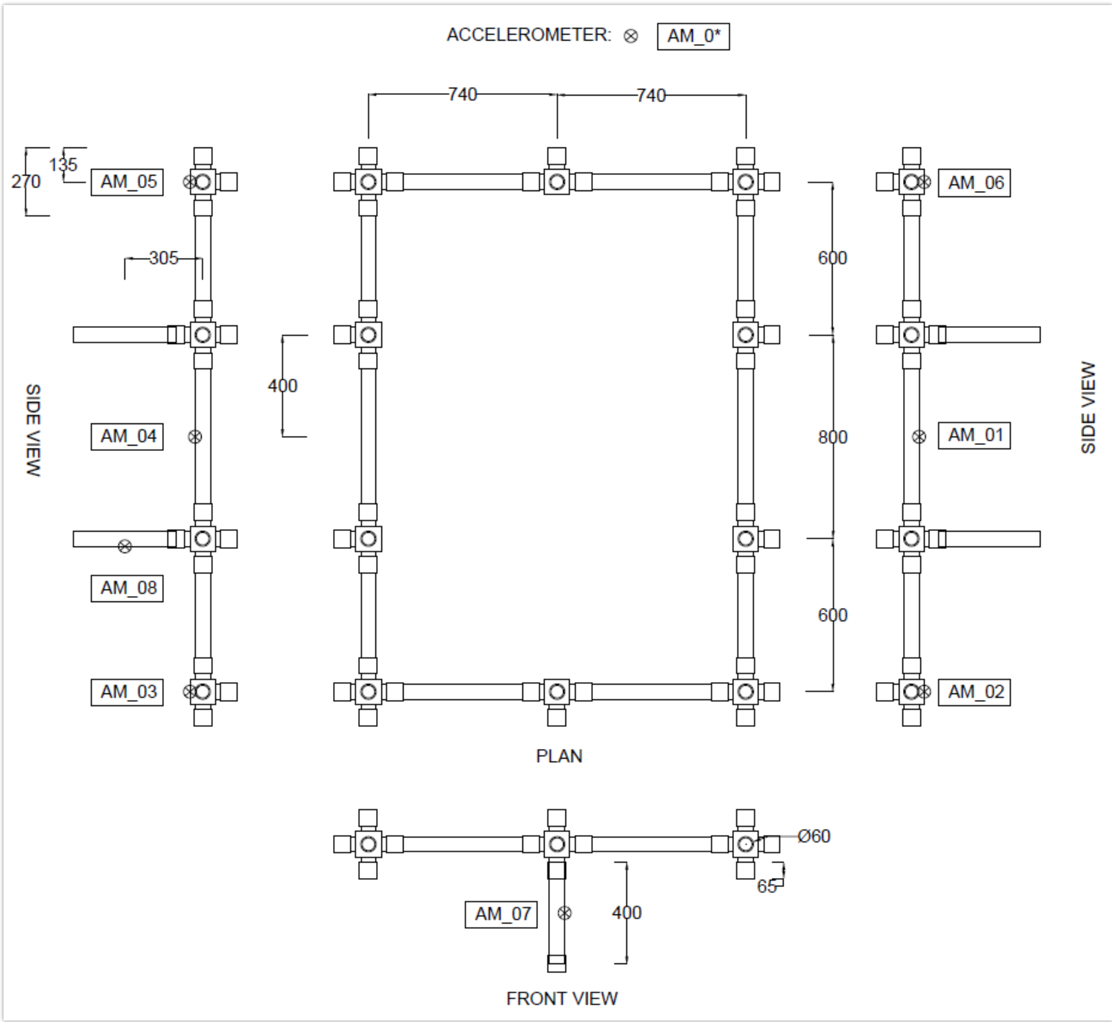


Figure 6.1 Sensor locations on the structural frame in the present study (All dimensions are in mm)

6.3 IMPLEMENTATION OF THE SENSOR PLACEMENT METHODOLOGY

The sensor placement methodology proposed in this study uses entropy to measure the information content of the data from a sensor location. Instead of raw data, features extracted for machine learning are used as variables for computing the entropy. Figure 6.2 shows the sensor placement methodology, and each step is described as follows.

Firstly, the 'Subset_List', which contains all the subsets of instances that need to be separated, is generated. The initial Subset_List consist of a single set of all the instances for identification (246 No.). Usually, the instances for sensor placement are generated during the pilot study. The current study uses the measurements from the eight initial sensor locations.

After creating the Subset_List, two lists of variables are created: 1) Vars_List for all the variables for construction monitoring, and 2) Sel_Vars for the selected variables from Vars_List during each iteration. The Sel_Vars is empty while the Vars_List contains eighty variables before the first iteration (This include ten distinct features from eight sensor locations. The unique features from each location are mean, variance, root mean square error (RMS), interquartile range (IQR), peak, three of the first main frequencies from Fast Fourier Transform (FFT), signal period, and signal energy). The name of each variable contains the name of the feature and the sensor location. For example, the variable name 'RMS_AM7' means the feature root mean square error of the acceleration data from location number seven.

The variable with maximum entropy is selected from the Vars_List and moved to Sel_Vars. The elements in the Subset_List are divided into children subsets at each iteration based on the distribution of the selected variable. Then the Subset_List is updated by replacing the current subset with its children subsets. The subsets which contain one instance or multiple instances of the same operation class are removed from the Subset_List. These steps are repeated until all the subsets are completely separated, or the Vars_List is empty. Finally, the optimal locations of sensors and features are identified from the selected variables in Sel_Vars.

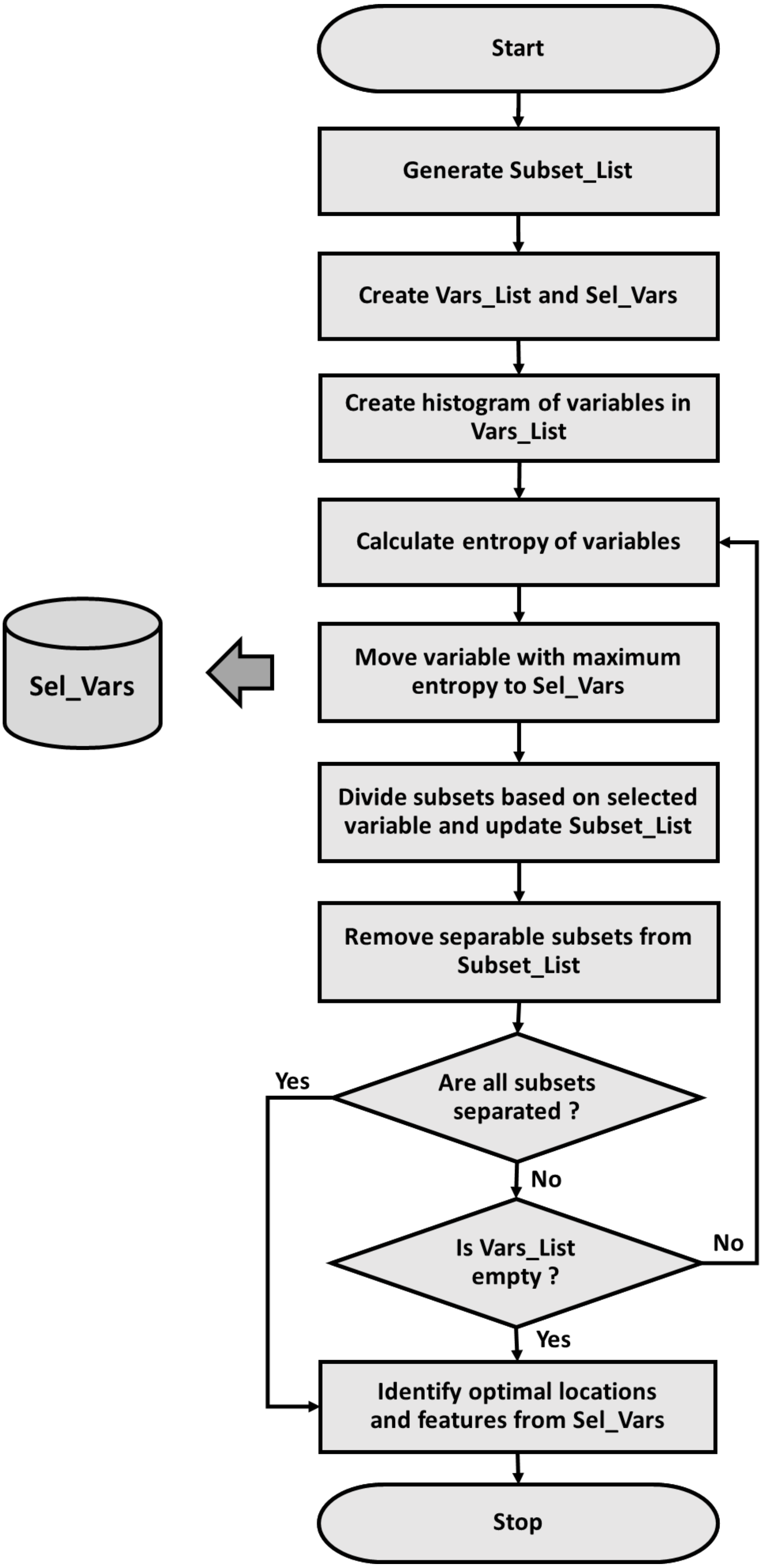


Figure 6.2 Sensor placement methodology

6.4 RESULTS AND DISCUSSION

6.4.1 Optimal sensor locations and features

The sensor placement methodology has selected eight optimal variables for automated construction monitoring. The maximum entropy of the variable at selection is given in Table 6.1. The initial subset in the Subset_List, which contained all the instances, has been iteratively divided into children subsets. The maximum entropy of a subset reduces while it is divided into children subsets. The iterative division continues until the children subsets are inseparable. Then the subsequent iteration starts with the separation of the next subset in the Subset_List. The maximum entropy of this newly selected subset also reduces with division. This trend can be observed in the entropy of the selected variable. After finishing all the iterations, 47 instances were completely identified. Other instances were separated into numerous inseparable subsets. This shows the potential of the selected variables to identify the automated construction operations even before complex data analysis.

Table 6.1 Variables selected by the sensor placement methodology

Rank	Selected variable	Maximum entropy of the variable at selection
1	RMS-AM7	2.155
2	IQR-AM7	2.007
3	IQR-AM5	3.019
4	IQR-AM1	3.788
5	IQR-AM8	3.559
6	3rd Prominent frequency-AM4	3.459
7	IQR-AM3	2.500
8	Mean-AM1	1.585

The order of selection of the variable with maximum entropy and corresponding scenarios are given in Table 6.1. The number of instances completely identified in each scenario is illustrated in Figure 6.3. Initially, the number of instances identified increased with the addition of variables. Then it decreased steadily after the addition of the fourth variable, except a slight increase with the addition of the sixth variable. The identification of instances did not improve considerably beyond four variables.

Table 6.2 The order of selection of the variable with maximum entropy

Scenarios	Variables used
1	RMS-AM7
2	RMS-AM7, IQR-AM7
3	RMS-AM7, IQR-AM7, IQR-AM5
4	RMS-AM7, IQR-AM7, IQR-AM5, IQR-AM1
5	RMS-AM7, IQR-AM7, IQR-AM5, IQR-AM1, IQR-AM8
6	RMS-AM7, IQR-AM7, IQR-AM5, IQR-AM1, IQR-AM8, 3rd Prominent frequency-AM4
7	RMS-AM7, IQR-AM7, IQR-AM5, IQR-AM1, IQR-AM8, 3rd Prominent frequency-AM4, IQR-AM3
8	RMS-AM7, IQR-AM7, IQR-AM5, IQR-AM1, IQR-AM8, 3rd Prominent frequency-AM4, IQR-AM3, Mean-AM1

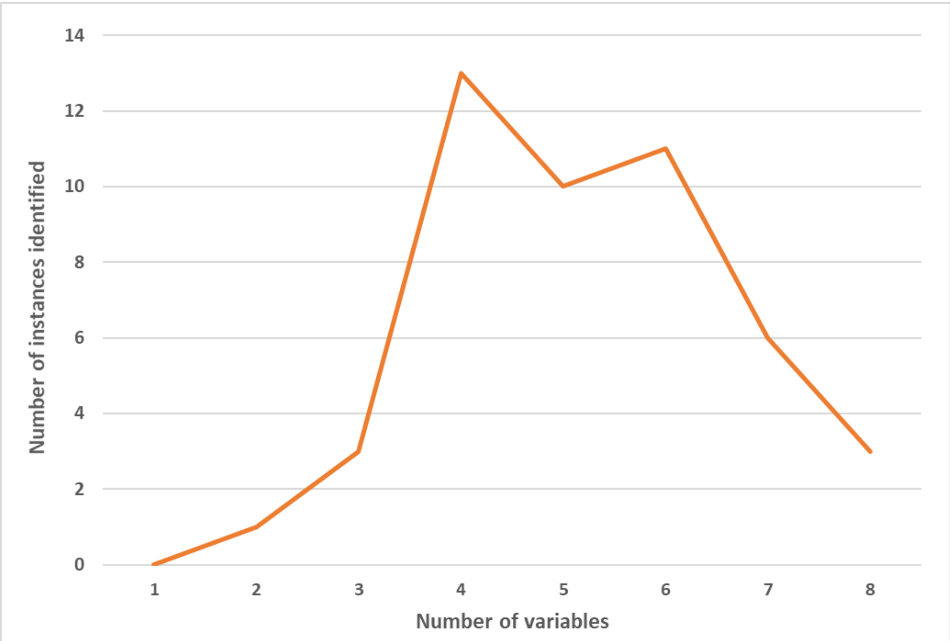


Figure 6.3 Variation in the number of instances completely identified with the addition of variables

The optimal sensors identified through the sensor placement methodology are presented in Table 6.3. Except for AM_02 and AM_06, all other sensors from the initial list are selected (Figure 6.1). The sensor placement methodology in this study considers the mutual information from a sensor and already selected sensors. Therefore, a particular sensor is selected only when it offers any new information. This may be the reason why AM_03 and AM_05 are selected while the diametrically opposite sensors, AM_02 and AM_06, are not selected. AM_02 and AM_06 are positioned at the corners of the long beams of the structure. Notably, the columns connected to this beam does not carry any sensors.

The sensor (AM_07) placed on the column connected to the short span offers the highest information for identifying operations. The vibrations from both sides of the column are captured effectively at this location. This location is followed by the sensor at the corner (AM_05) and midspan (AM_01) of the structure. Different type of measurement locations is selected during each iteration of this sensor placement methodology. Therefore, adding a new sensor is based on its mutually exclusive information content from the previously selected sensors. In addition to AM_07, AM_01 is the most frequently selected sensor.

Table 6.3 Location of sensors selected by the sensor placement methodology

Serial number	Sensor	Frequency of occurrence in the selected variables
1	AM_07	2
2	AM_05	1
3	AM_01	2
4	AM_08	1
5	AM_04	1
6	AM_03	1
7	AM_02	0
8	AM_06	0

The features selected through the sensor placement methodology is presented in Table 6.4. Interquartile range (IQR) is the most frequently selected feature among the ten unique features extracted from a sensor location. The calculation of entropy is based on the histogram of the variables. Therefore, IQR appears to be the most prominent feature. However, machine learning classification may demand more complex frequency domain features to distinguish the operation categories. One of such features, 3rd prominent frequency, is selected by this method. Some of the features such as peak and 1st prominent frequency are intuitively significant for identifying operation signals. But these features are not selected by this proposed method. Therefore, additional information may be required to determine the suitable features using this method.

Table 6.4 Features selected by the sensor placement methodology

Serial number	Feature	Frequency of occurrence in the selected variable
1	RMS	1
2	IQR	5
3	3rd Prominent frequency	1
4	Mean	1
5	Variance	0
6	Peak	0
7	1st Prominent frequency	0
8	2nd Prominent frequency	0
9	Signal energy	0
10	Main signal period	0

6.4.2 Validation of sensor placement methodology

The proposed sensor placement methodology is validated by recognising automated construction operations using the derived measurement configuration. Artificial Neural Networks are deployed to identify the operations of the Automated Construction System prototype. The conventional approach for activity recognition is adopted to verify the effectiveness of the proposed measurement configuration. Forty-one operation classes at classification level 4 are identified during validation. Three feature selection methods (FS1, FS2 and FS3) based on the information from the sensor placement methodology are used for operation identification. The overview of these methods is provided in Table 6.5. The purpose of feature selection includes simplifying the prediction model and reducing the computational effort by reducing the number of features. The best features that help to create a generalisable model are determined through feature selection. The performance of the feature selection methods is compared with that of the machine learning classification with all of the variables (FS0).

Table 6.5 Overview of feature selection methods for the validation of the sensor placement methodology

Serial no.	Total no. of features selected	Information from the sensor placement methodology	Feature selection method	Unique features selected	Sensors selected
FS0	80	-	All of the initial variables as features	Mean, variance, Peak, IQR, RMS, Signal energy, Main signal period, 1st Prominent frequency, 2nd Prominent frequency, 3rd Prominent frequency	1 to 8
FS1	60	Sensor locations	All of the unique features extracted from the sensors selected through sensor placement methodology	Mean, variance, Peak, IQR, RMS, Signal energy, Main signal period, 1st Prominent frequency, 2nd Prominent frequency, 3rd Prominent frequency	1,3,4, 5,7,8
FS2	32	Features	Features selected through sensor placement methodology extracted from all sensors	Mean, IQR, RMS, 3rd Prominent frequency	1 to 8
FS3	8	Sensor locations and features	Variables selected through sensor placement methodology as features	Mean, IQR, RMS, 3rd Prominent frequency	1,3,4, 5,7,8

The results of operation identification are presented in Table 6.6, and the performance comparison is illustrated in Figure 6.4. The feature selection method FS1 uses the information about sensor locations from the sensor placement methodology. This method reduces 25 per cent of features for machine learning classification. However, the reduction in F1 score is merely 3.42 per cent, and that of accuracy is 5.28 per cent. Thus, the proposed sensor placement methodology effectively selects the appropriate measurement configuration for automated construction monitoring.

Table 6.6 Performance of feature selection methods

Serial no.	Information from the sensor placement methodology	Precision (%)	Recall (%)	F1Score (%)	Accuracy (%)
FS0	-	79.84	84.63	82.12	84.56
FS1	Sensor locations	77.32	81.71	79.31	80.10
FS2	Features	68.05	72.68	70.25	71.58
FS3	Sensor locations and features	65.00	72.20	68.37	71.11

FS2 evaluates the ability of the proposed sensor placement methodology for feature selection. FS2 reduces 60 per cent of features with a 14.45 per cent reduction in F1 score and a 15.36 per cent reduction in accuracy. The results demonstrate reasonably good performance for feature selection. However, most of the features selected through this method are time domain features, more specifically IQR, as shown in Table 6.4. The reason for this selection is attributed to the use of entropy for sensor placement. Therefore, additional information about frequency domain features enhance the current feature selection.

The last feature selection method FS1 extracts sensor locations and features from the sensor placement methodology and reduces 90 per cent of features. Nevertheless, the reduction in performance is at par with that of FS2 (reduction in F1 score and accuracy are 16.75 per cent and 15.91 per cent, respectively). Therefore, the proposed sensor placement methodology is beneficial for applications scenarios involving hundreds of sensors. The cost of measurement can be considerably reduced with a reasonable reduction in accuracy. In addition to determining measurement configuration, this method can be applied to select features and improve computational efficiency whenever required.

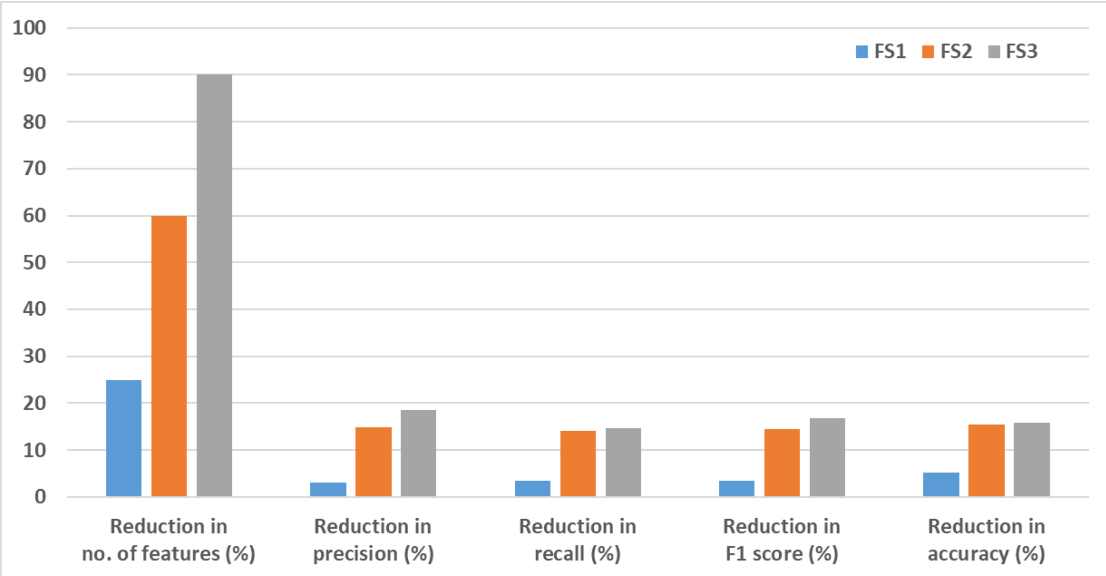


Figure 6.4 Comparison of feature selection methods

The concept of sensor placement based on Shannon's entropy was initially proposed by Robert-Nicoud *et al*.(Robert-Nicoud *et al.*, 2005). The current methodology departs from the existing study in terms of variables and the objective of measurement system design. The previous studies used this approach to separate model classes for falsification (Kripakaran, Saitta, *et al.*, 2007; Kripakaran and Smith, 2009; Papadopoulou *et al.*, 2016; Bertola and Smith, 2019), whereas the current study focuses on instance classification. While the existing studies use the distribution of raw data for location selection (Kripakaran, Ravindran, *et al.*, 2007; Soman *et al.*, 2015), the current study incorporates the features for identification. Joshua and Varghese used a decision tree algorithm and body segment analysis to determine the measurement locations for human activity recognition (Joshua and Varghese, 2013). The average accuracy of the measurement configuration proposed by that study for identifying construction activities was 77.99 per cent. The current study significantly improves the activity recognition performance (80.10 per cent accuracy for FS1) by incorporating features for entropy calculation.

The proposed sensor placement methodology has demonstrated its ability for selecting features and determining measurement locations. The final measurement configuration has to be decided based on the trade-off between cost and measurement accuracy. The current study aims to develop a monitoring system for automated construction; high accuracy is crucial for selecting measurement configuration. Besides, the focus of the next set of studies is not feature selection. Therefore, all sensor locations and features are selected to ensure the highest possible performance for each algorithm/identification method. No higher computational cost is incurred by incorporating these features. The measurements from the two sensors that are not selected are available without additional cost and are included for further analysis.

6.5 CONCLUSIONS

The configuration of the measurement system significantly affects the quality of data collected for construction monitoring. The current study proposes a sensor placement methodology based on information content from the measurement locations. The entropy of the features extracted from the raw measurements determines the selection of a location.

1. The proposed sensor placement methodology determines optimal measurement locations for identifying automated construction operations. The sensor

locations selected based on this methodology delivered a 79.31 per cent F1 score and 80.10 per cent accuracy for operation identification.

2. The proposed sensor placement methodology also demonstrates its potential for feature selection. The feature selection method based on this sensor placement methodology reduces 90 per cent of the features with merely a 15.91 per cent reduction in accuracy.

3. The addition of variables beyond a certain threshold during sensor placement does not improve the identification of instances. A particular sensor is selected in an iteration only when it offers any new information.

4. Each iteration of the sensor placement methodology selects different types of measurement locations. The order of selection of new sensors is based on their mutually exclusive information content from the previously selected sensors.

5. The method of calculating the information content of a measurement location influences the features selected by the sensor placement methodology. The entropy is calculated based on the distribution of the variables. Therefore, the interquartile range is the most frequently selected feature among the variables.

CHAPTER 7

ANALYSIS AND RESULTS: OPERATION IDENTIFICATION

7.1 INTRODUCTION

A fundamental step in developing an automated monitoring system is operation identification. The operation identification methodology developed for automated construction is discussed in this chapter. In this thesis, the term 'Operation' refers to low-level activities related to the use of construction equipment. These low-level activities might be considered as subparts in the decomposition of higher-level construction activities. The activities of construction equipment were identified for various purposes in the existing studies. Some of these include computation of cycle time of operations; estimation of fuel consumption, emission rate or productivity of equipment; assessment of the condition of equipment and construction progress monitoring (Harichandran *et al.*, 2018; Kim and Chi, 2019; Chen *et al.*, 2020). Most existing studies consider equipment activity recognition as a classification problem. The input consists of a time series of sensor data, and the output variables represent the activity classes to be identified. Typically, a flat list of activity classes is used for training the machine learning model.

This study departs from the existing studies in the objective of operation identification and its problem formulation. The main objective of equipment operation identification for the current study is to develop a construction monitoring system. Therefore, accuracy is of the utmost importance. Besides identifying the construction activity, detailed information about construction and equipment is essential for corrective measures. Therefore, the current study proposes a hierarchical identification methodology for operation identification. This methodology utilises the hierarchical activity relationships for the formulation of the identification problem. This modified problem formulation simplifies the identification task and improves accuracy. The identification methodology is tested on the Automated Construction System (ACS) prototype for low rise building construction. The acceleration data from the structure is used for supervised learning. Each identification task is solved using six machine learning algorithms (k-Nearest Neighbour, Decision Tree, Support Vector Machines, Discriminant Analysis, Naïve Bayes, Artificial Neural Network) for determining the best classifier. The performance of the proposed methodology is compared with that of the conventional approach for equipment operation identification, which involves a flat list of classes to be separated. The possibility of using raw measurement data and deep learning classifiers for the current identification problem is also explored.

The rest of the chapter is organised as follows: Section 7.2 presents machine learning-based operation identification, including selecting the appropriate machine learning classifier and the identification methodology. The operation identification based on deep learning is described in section 7.3. A detailed analysis of the results and related discussions are presented in section 7.4. The generalizability of the proposed operation identification methodology is outlined in section 7.5. Finally, the significant findings of the study are concluded in section 7.6.

7.2 MACHINE LEARNING-BASED OPERATION IDENTIFICATION

The overall methodology for hierarchical identification of automated construction operations is shown in Figure 7.1. First, sensor data from the structure is collected during controlled experiments. The raw data are then subjected to pre-processing followed by feature extraction for supervised learning. The next stage is machine learning classification and operation identification. The novel hierarchical operation identification methodology adopted in this study is described in the next paragraph. The output of the hierarchical operation identification is supplied to an automated construction monitoring system. The monitoring system further evaluates the identified operations for potential anomalies and signals the operator for necessary corrective actions. The scope of the current chapter is limited to operation identification. The fault detection for automated construction operations is discussed in the next chapter.

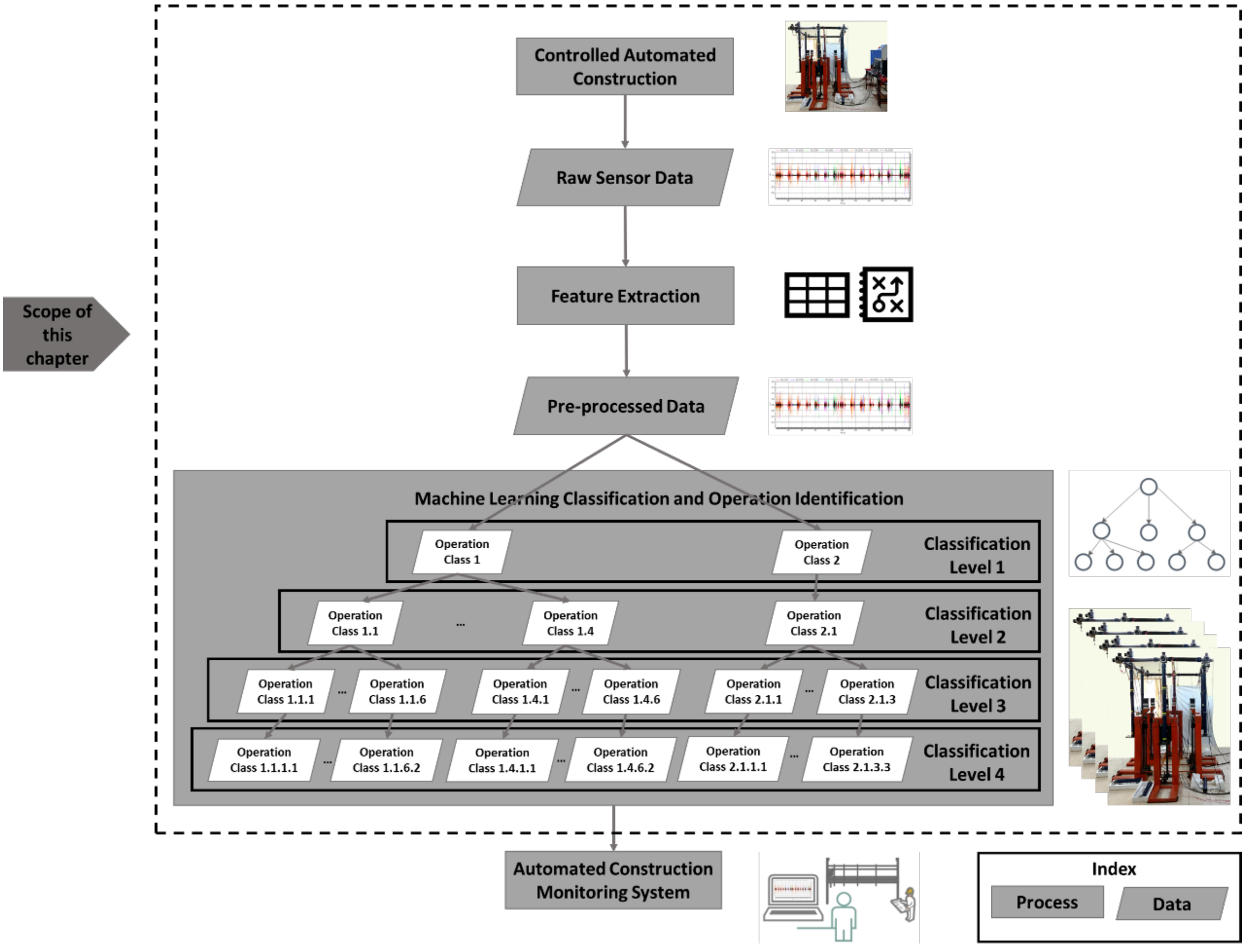


Figure 7.1 Methodology for identification of automated construction operations

Operations are hierarchically decomposed in the proposed identification methodology, using domain knowledge about the construction equipment and types of operations. A schema containing operations, states of the equipment and their hierarchical relationships is developed first. Activities at the top level are general; specialised operations with more details appear at lower levels. Operation identification occurs in multiple stages, starting from the topmost level. The identification methodology uses multiple machine learning classifiers at each level. A single machine learning model (classifier) is not used to separate all the classes. Instead, a new classifier is used to explore the subclasses of a previously identified operation class.

7.2.1 Selection of machine learning classifier

Machine learning techniques are widely used for solving activity recognition problems using sensor data. Supervised learning methods were observed to deliver better results than unsupervised learning methods for activity identification problems (Golparvar-Fard *et al.*, 2013). According to Akhavian and Behzadan, unsupervised learning methods tend to cause overfitting during classification with imbalanced equipment activity classes (Akhavian and Behzadan, 2015). The classification of automated construction operations is similar to that of construction equipment in imbalanced activity classes. Hence supervised learning methods are adopted for this study. Deep learning methods show promising results for equipment activity identification. However, these methods demand large datasets for training. Automated construction experiments are costly and time-consuming. It is not practical to generate large datasets by experiments. Augmentation of data also requires expert knowledge, and the generated datasets should capture the possible working conditions of automated construction. The evaluation of deep learning techniques for this task is discussed in Section 7.3. The current section explores the possibility of using a well-established machine learning technique for identification of automated construction operations. It is essential to evaluate the attributes of the classifier for precise identification of automated construction operations. Given the limited experimental data, the classifier should have good generalisability without overfitting. The acceleration patterns measured are a complex combination of the vibration from the structure and the ACS during construction. The classifier should be able to learn the nonlinear relationship between the acceleration measurements from different locations of the structure and the automated construction operations. The classifier should have clear parameters to indicate the confidence for the predicted results so that necessary control actions can be taken during construction monitoring. Based on the above requirements, a study was carried out to determine the best learning algorithm for operation recognition. The results of this study are presented in section 7.4.1. Artificial Neural Network (Feed-forward classification network) is selected as the classifier for identification of automated construction operations. It was identified that ANN delivers the best performance at all classification levels. Therefore, further studies to validate the identification methodology was performed using ANN.

7.2.2 Methodologies for operation identification

This study evaluates two different problem formulations for the identification of automated construction operations. The first is the conventional approach adopted in previous studies (Figure 7.2), and the second is the hierarchical methodology proposed in the current study (Figure 7.3). Both methodologies are evaluated for their ability to identify operations at four classification levels. All the operation classes are supplied as a flat list to the conventional approach. However, the identification is separated into four levels to compare its performance with the hierarchical methodology. The operations are classified into finer subclasses from the top level to the bottom level. Classification level 1 consists of the operation states of the ACS, namely, idle and operations. The idle state indicates that the automation system is turned on, but no operations are being performed. The data generated in this state is primarily due to ambient vibrations. Classification level 2 further divides the operations into four major classes. Classification level 3 contains the subclasses of operations. It divides two operations (lifting and lowering) into subclasses based on which the lifting machine operates. The 'connection of column module' operation is divided based on which column is being constructed at that time. All operations are subdivided at classification level 4 based on the stage of construction at which the operation was performed.

7.2.2.1 Conventional approach

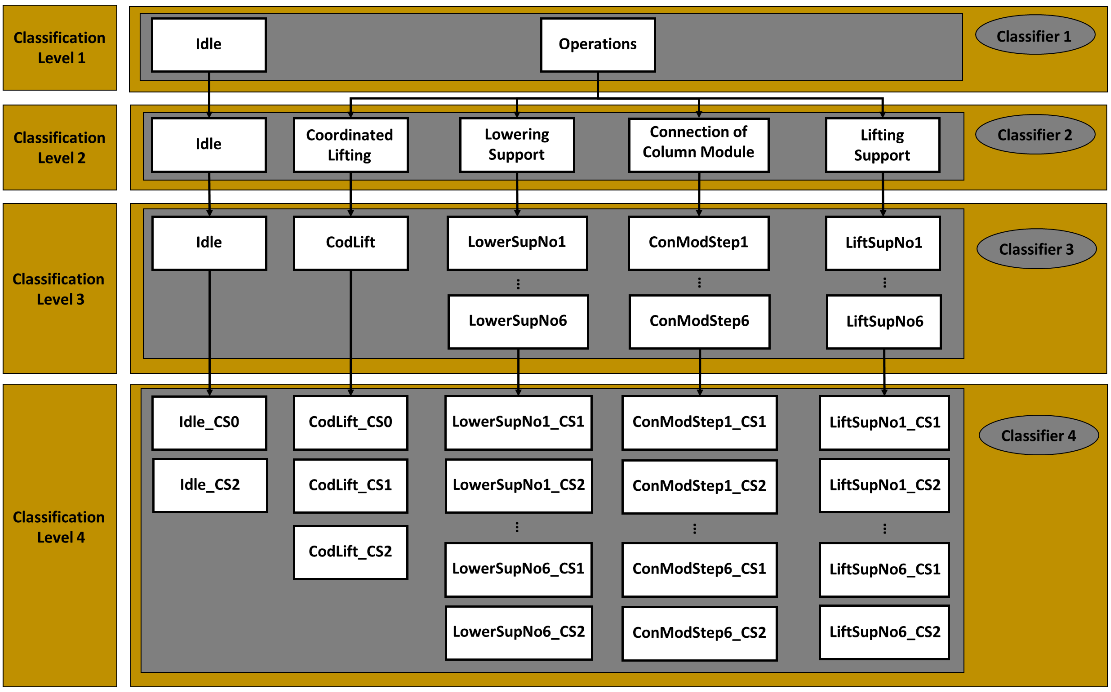


Figure 7.2 The conventional approach for operations identification in which the classifier uses a flat list of classes. Multiple classification levels were deployed for performance comparison with the hierarchical methodology.

The conventional approach containing a flat list of classes is shown in Figure 7.2. A classification level contains one identification task (classification problem). A machine learning classifier is a predictive model developed and trained to solve a classification problem in the current context. One machine learning classifier per classification level is shown in Figure 7.2 (Classifier 1, Classifier 2, …, Classifier 4). The yellow boxes represent the classification levels. The grey boxes represent machine learning classifiers at a classification level. The white boxes are the operations classified by a particular machine learning classifier. Most previous studies have adopted this problem formulation for operation identification (Akhavian and Behzadan, 2015; Rashid and Louis, 2019; Shi *et al.*, 2020). It does not use any prior information from the previous classification level. As the classification level increases, the complexity of the learning task also increases. Classification level 1 has only two operations, while classification level 4 has 41 operations. This conventional approach for identification seems to give good performance only when the number of operation classes is small. As the number of similar operation classes increases, performance appears to be consistently declining. The initial classification was performed using the conventional approach to verify its suitability for identifying a large number of classes.

7.2.2.2 Hierarchical operation identification

The hierarchical methodology for identification proposed in this study formulates the identification problem into a hierarchy of learning tasks (Figure 7.3). Each classification level in this identification methodology uses prior information from the previous classification level to simplify the identification task. There can be more than one identification task per classification level. Accordingly, there is a hierarchy of machine learning classifiers, each assigned to solve an identification task. There are 25 machine learning classifiers numbered systematically as 'Classifier L.N' where L represents the classification level, and N represents the number of the classifier at classification level L. Each machine learning classifier classifies similar operations at a particular level.

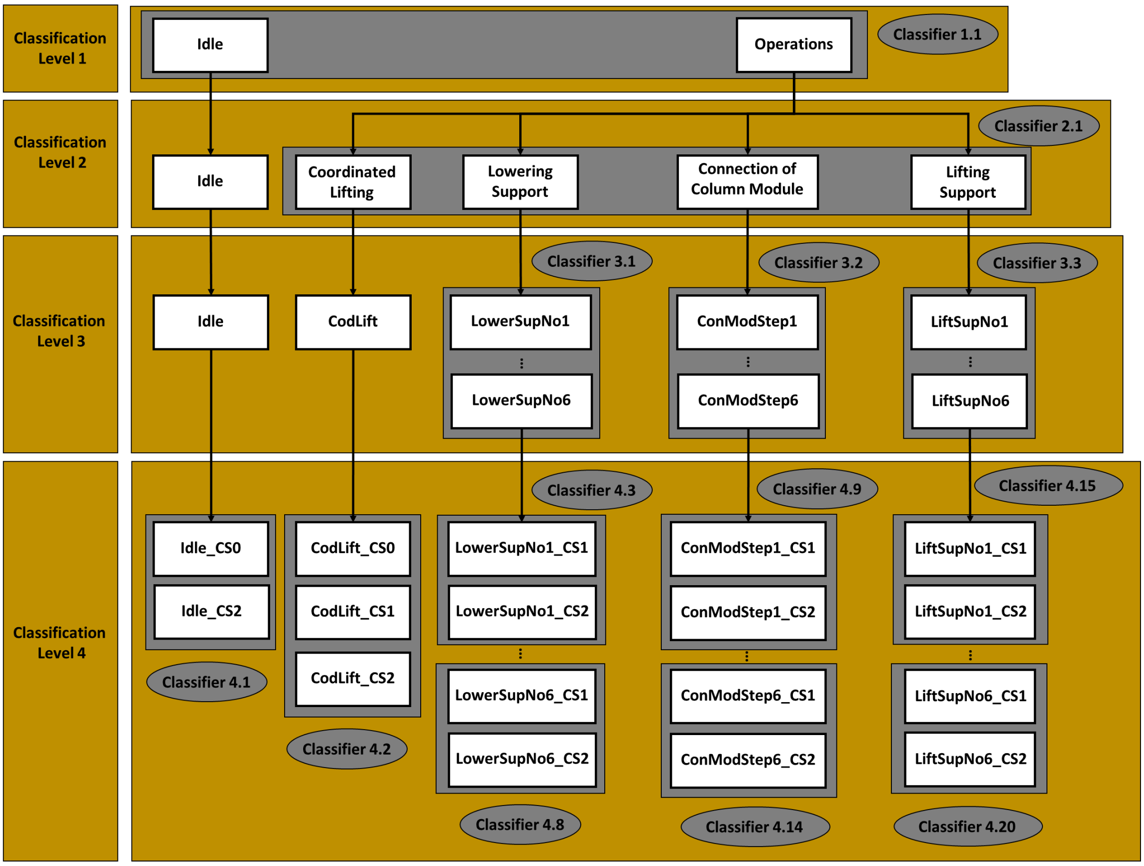


Figure 7.3 Hierarchical methodology for operation identification that arranges the operation classes into multiple classification levels based on their hierarchical relationship. Each classification level may contain more than one classifier.

The identification tasks for the hierarchical methodology are formulated based on the logical flow of information required in an automated monitoring system, represented by black arrow marks in Figure 7.3. Consider this example for the flow of information and measured data through classification levels: A particular operation is going on in the automated construction. The monitoring system identifies the status of the ACS as 'Operations' at classification level 1 (Classifier 1.1). Now, the main operation needs to be identified in the following classification level. The class 'Idle' can be removed from the further identification tasks to simplify the problem (Classifier 2.1). If the main operation is identified as "Lifting Support" in classification level 2, only the sub-classes of "Lifting Support" need to be investigated for further classification. This means that there should be specific identification tasks for each subclass of the main operation. The sensing data will be redirected to a particular identification task based on the prior information from the previous classification level. In this way, there are three simple machine learning classifiers (Classifier 3.1, Classifier 3.2, Classifier 3.3) in the hierarchical methodology instead of one complex machine learning classifier (Classifier 3) in the conventional approach at classification level 3. Each classifier solves an identification task with six classes instead of one classifier that solves an identification task with 20 classes. In the previous classification level, the operation is identified as "Lifting Support". Now, the sensing data will be redirected to classifier 3.3 for further classification. If the operation is identified as "LiftSupNo6" at classification level 3, the next classifier in classification level 4 will be classifier 4.20. This classifier will identify the operation based on the construction stage (LiftSupNo6_CS1 or LiftSupNo6_CS2).

The first two classification levels have only one machine learning classifier, each in the hierarchical identification methodology. Classifier 1 (conventional approach) and classifier 1.1 (hierarchical methodology) are essentially the same. Classifier 2 is slightly different from classifier 2.1 since it also included 'idle' in classification along with the operations. Classifier 3 is replaced by classifier 3.1 to classifier 3.3 (3 classifiers), and classifier 4 is replaced by classifiers 4.1 to classifier 4.20 (20 classifiers) in the hierarchical methodology. The purpose of designing this complex methodology is to develop robust machine learning classifiers for each classification level. The overall objective of this operation identification is to develop an automated monitoring system. Ensuring high accuracy in operation identification will reduce the possibility of false alarms during monitoring and decrease the chances of not reporting any faulty operation. This will eventually reduce workplace accidents.

7.2.3 Evaluation of performance

The performance of each classifier is evaluated through k-fold cross-validation to avoid dependency on a particular dataset or overfitting. In k-fold cross-validation, data is arbitrarily split into k folds. Then, one fold is reserved for validation (used as unseen data) and the others are used for training. Next, another fold is used for validation, while the remaining folds are used for training. This process is repeated k times until all the folds are used for validation once. Each performance parameter of the cross-validated classifier is computed as an average of that parameter from all the folds. The classifiers in the first three levels of classification are 10-fold cross-validated. The classifiers in classification level 4 are 5- fold cross-validated since the number of data points is less.

Accuracy, precision, recall and F1 Score are the parameters used to assess the performance of a classifier. Accuracy is the percentage of data points correctly identified out of the total number of data points (equation (7.1)). Identification accuracy is an overall estimate of the performance of a classifier. Precision and recall are computed to investigate the relevance of the information retrieved by a classifier. Precision is also known as Positive Predictive Value (PPV). It is the percentage of the identifications which are relevant out of all the identification results (equation (7.2)). The recall is also called the true positive rate. In other words, it is the percentage of the relevant operation classes correctly identified by the classifier (equation (7.3)). F1 Score is the harmonic mean of these two parameters (equation (7.4)).

$$Accuracy = \frac{Number\ of\ correctly\ identified\ datapoints}{Total\ number\ of\ datapoints}\ x\ 100\ \% \qquad (7.1)$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive}\ x\ 100\ \% \qquad (7.2)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative}\ x\ 100\ \% \quad (7.3)$$

$$F1\ Score = \frac{2\ x\ Precision\ x\ Recall}{Precision + Recall} \quad (7.4)$$

7.3 DEEP LEARNING BASED OPERATION IDENTIFICATION

Even though the construction industry is generally conservative regarding technological adoption, the research community is ardent in exploring the latest technological possibilities. Several recently published literatures seem to advocate the adaptation of complex deep learning techniques over traditional machine learning algorithms regardless of the application context. Machine learning often requires domain expertise in selecting good features. However, deep learning algorithms learn the characteristics features directly from raw data. Therefore, the potential of deep learning algorithms in identifying automated construction operations was explored.

The methodology adopted in this study for identifying automated construction activities is shown in Figure 7.1. An approach based on deep learning classification is implemented along with traditional machine learning classifiers. First, the automated construction operations were performed by the ACS under controlled laboratory conditions. The sensor data were collected from different parts of the structure during construction. The collected data were subjected to pre-processing followed by supervised learning. The raw data were augmented to create a larger dataset for deep learning classification. Concurrently, features were extracted from the dataset for machine learning classification. The current study classifies the time series sensor data using LSTM networks. The traditional machine learning classifiers include k-Nearest Neighbour (kNN), Decision Tree (DT), Support Vector Machines (SVM), Discriminant Analysis (DA), Naïve Bayes (NB), and Artificial Neural Network (ANN). Finally, all of these classifiers were assessed for their performance in identifying automated construction activities. In the broader context, deep learning is a subset of machine learning. For clarity in discussions, the author refers to the traditional machine learning classifiers under 'machine learning' and advanced deep learning methods under 'deep learning'. The data augmentation methods used in the study and LSTM network training is described in detail in the following subsections.

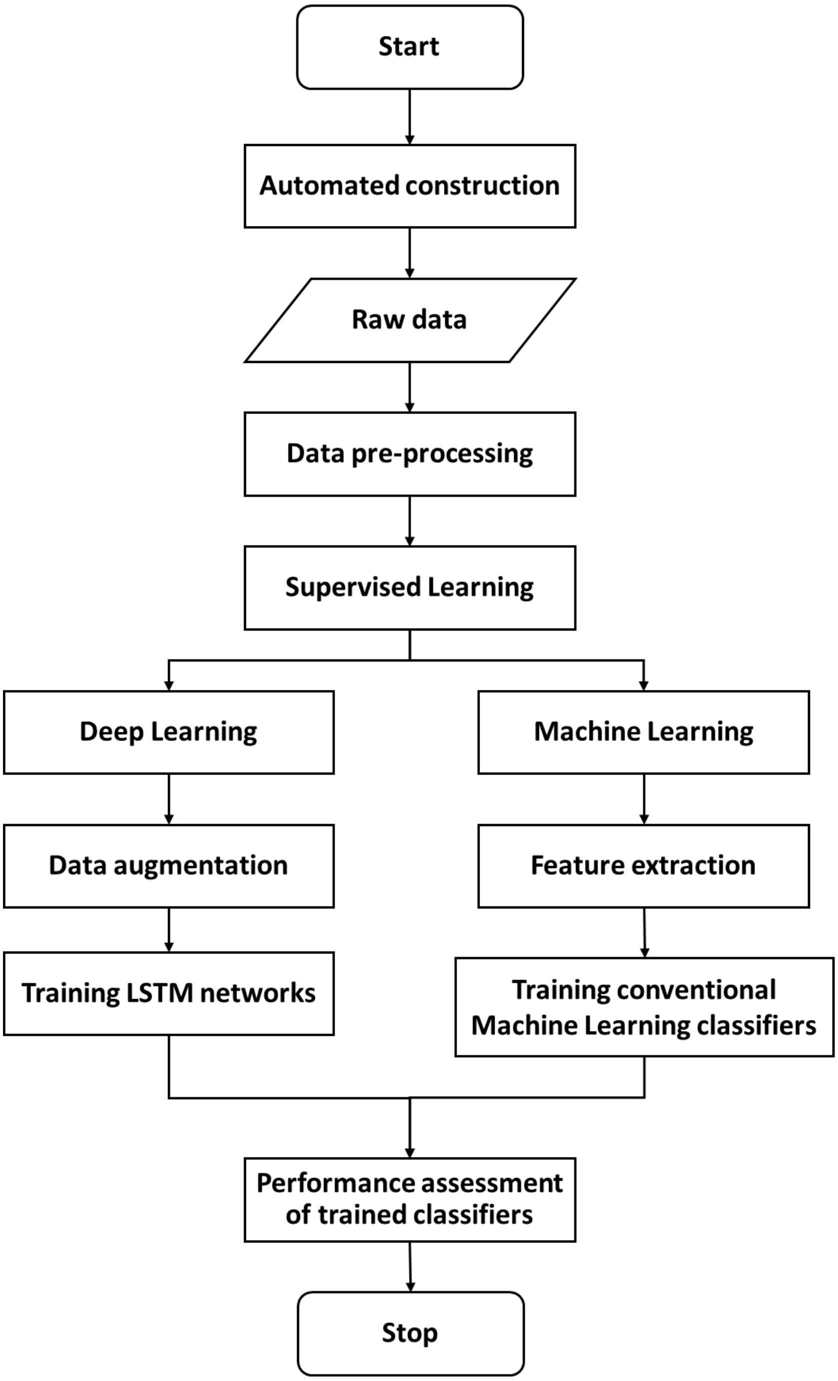


Figure 7.4 Methodology adopted for comparing the performance of deep learning classifiers with conventional machine learning classifiers

7.3.1 LSTM networks

The data collected in the current study is in the form of time series signals. Long Short-Term Memory (LSTM) networks are best suited to classify this type of data since they learn to identify long term dependency between timesteps of a signal (Hochreiter and Schmidhuber, 1996, 1997; Hochreiter, 1998; Arras *et al.*, 2019). The current study adopted a Bi-LSTM (bidirectional LSTM) network that learns the complete information of the signal at each time step. The architecture of the network for the current classification problem is shown in Figure 7.5. The first layer is a sequence input layer that inputs the raw acceleration data into the network. This layer is followed by a Bi-LSTM layer which learns the long-term bidirectional dependency between timesteps of the input data. The last three layers, namely, the fully connected layer; SoftMax layer; and classification layer enable the network to predict the class labels.

Figure 7.5 Architecture of LSTM network for operation identification

7.3.2 Data augmentation methods

Deep learning methods are known to deliver the best results when there is abundant data available for training. Since there are numerous publicly available datasets of common objects, training deep neural networks to detect these objects may not pose a challenge. Creating large datasets of specific objects like common construction equipment (excavator, dump truck, tower crane etc.) may be a little more challenging compared to that for common objects. This data shortage can be addressed by generating new data through the augmentation of the existing data. Flipping, rotation, cropping etc., are some of the widely used data augmentation methods for image data.

The newly generated images create significant variations in the original datasets without altering the original labels. However, augmenting time series data may not be as intuitive as image datasets (Rashid and Louis, 2019). The newly generated signals should not vary the fundamental characteristics of the original signal in such a way that it may alter the original label. The variability introduced by random noise, method of execution and data collection method retains the original labels of the signal. Therefore, the current study introduces these variabilities by jittering, scaling, down sampling and over sampling of the measured data.

7.3.2.1 Jittering

The variability in time series data due to additive sensor noise is introduced through jittering (Rashid and Louis, 2019). White Gaussian noise is incorporated in the raw data to create the jittered dataset (Stahel and Maechler, 2021). The amount of noise varies from -SF * DF/5 to SF * DF/5, where DF is the smallest difference between the values of the measured data and SF is a scaling factor. The value of SF adopted in the current study ranges from 2 to 19.

7.3.2.2 Scaling

The intensity of vibration corresponds to each construction operation changes with variability in its execution; this variability is introduced through scaling. In scaling, the magnitude of the measured data is altered by multiplying the signal by a scalar (Rashid and Louis, 2019). The scalar value for the current study ranges from 0.3 to 2.1.

7.3.2.3 Down sampling

The measurements for operation identification can be collected at different sampling rate with varying information contents. Down sampling reduces the sampling rate of the measured data by an integer factor. This data augmentation method is used sparingly to retain the necessary information content for classification. Therefore, the reduction factor ranges from two to five in the current study.

7.3.2.4 Over sampling

Imbalance in training datasets significantly affect the learning process and often result in high misclassifications of minority classes. Therefore, oversampling is adopted as a measure to balance the distribution of classes in the datasets. The instances of the underrepresented classes were duplicated in the oversampling. This augmentation method is used independently and in addition to other methods to create new datasets.

7.4 RESULTS AND DISCUSSION

7.4.1 Determination of the best learning algorithm for operation identification

There are 25 machine learning classifiers in the hierarchical identification methodology, each corresponding to an identification task. The classifiers were tested with six different machine learning algorithms to determine the best performing algorithm. The best identification results of each learning algorithm are presented in this section. The results of operation recognition for identification level 1 are summarised in Table 7.1 and illustrated in Figure 7.6. Classifier 1.1 identifies the idle and operating states in automated construction. All the learning algorithms have identification accuracy above 95 per cent. Even though slightly lower, the F1 Score also follows a similar trend of accuracy, except for DA. The ANN has the best overall performance in terms of accuracy and relevance of information retrieval. SVM seems to have high accuracy (95.528 per cent) even though it is slightly lower than other learning algorithms. But the precision and recall are considerably lower than those of the other algorithms. This is the first identification task in this identification methodology. The performance of the classifier in this task highly influences the performance of the overall methodology.

Table 7.1 Results of operation identification for identification level 1 (Classifier 1.1)

Learning algorithm	Precision (%)	Recall (%)	F1 Score (%)	Accuracy (%)
kNN	82.906	89.153	85.916	97.561
DT	91.026	88.032	89.504	97.967
SVM	66.026	76.898	71.048	95.528
DA	90.171	78.975	84.202	96.341
NB	78.739	87.834	83.038	97.154
ANN	95.000	94.792	94.894	99.583

Notes: kNN = k-Nearest Neighbour; DT = Decision Tree; SVM = Support Vector Machines; DA = Discriminant Analysis; NB = Naïve Bayes; ANN = Artificial Neural Network.

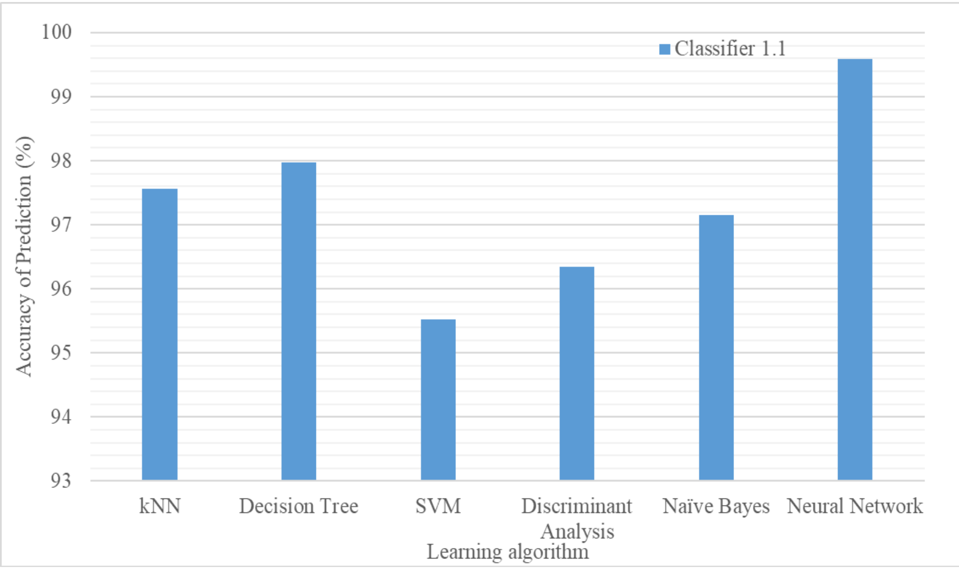


Figure 7.6 Accuracy of prediction for identification level 1

The operation recognition results of identification level 2 are given in Table. 7.2 and Figure 7.7. Classifier 2.1 distinguishes the major operation category of the given input data. The ANN identifies the operations with 100 per cent accuracy and an F1 score. This classifier has a simple network architecture: 11 neurons and one hidden layer. All the performance indices demonstrate a similar trend in performance for the rest of the learning algorithms. SVM and DA show comparable performance for this identification task. They have the next to best performance compared to other learning algorithms, contrary to identification level 1. The interesting observation is that both SVM and DA follow discriminant or boundary-based classification strategy. SVM used a polynomial kernel function for the current identification task, whereas DA used a linear discriminant. All other learning algorithms show less than 95 per cent accuracy and F1 Score for this identification task. Compared to the results in identification level 1, all classifiers improved their F1 Score. Even though accuracy is reduced, the relevant information retrieval improved.

Table. 7.2 Results of operation identification for identification level 2 (Classifier 2.1)

Learning algorithm	Precision (%)	Recall (%)	F1 Score (%)	Accuracy (%)
kNN	94.097	94.335	94.216	92.735
DT	94.792	94.781	94.787	94.872
SVM	98.264	97.305	97.782	97.863
DA	97.222	97.406	97.314	96.581
NB	92.014	94.231	93.109	92.735
ANN	100.000	100.000	100.000	100.000

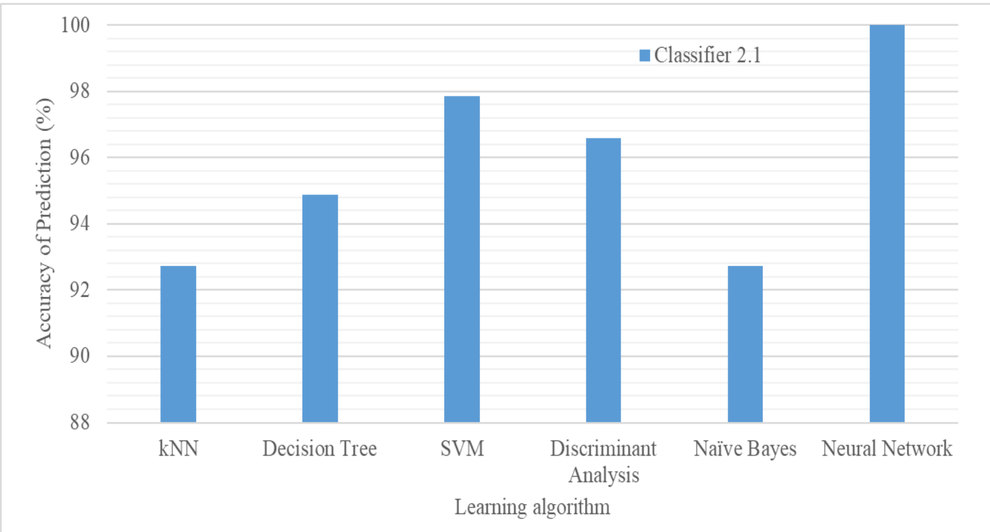


Figure 7.7 Accuracy of prediction for identification level 2

Identification level 3 comprises three classifiers; each classifier is assigned to identify the sub-operation categories. Each identification task contains six categories with an equal number of instances. Hence the classifiers need not face problem associated with unbalanced datasets. A stark difference in the performance of ANN from other learning algorithms is evident from the current identification level (Table. 7.3 and Figure 7.8). The ANN delivers close to 100 per cent accuracy and F1 Score for all classifiers. Except for Classifier 3.2 using kNN, all other algorithms demonstrate a considerable decline in identification performance. The main reason for this decline may be due to the higher similarity among sub-operation classes compared to that in the previous identifications tasks. As the complexity of identification increases, all learning algorithms except ANN fail to achieve the necessary performance required for this identification task.

Table. 7.3 Results of operation identification for identification level 3

Learning algorithm	Precision (%)		
	Classifier 3.1	Classifier 3.2	Classifier 3.3
kNN	83.333	97.222	88.889
DT	66.667	68.056	72.222
SVM	77.778	93.056	86.111
DA	77.778	90.278	87.500
NB	77.778	91.667	84.722
ANN	98.333	100.00	99.167
Learning algorithm	Recall (%)		
	Classifier 3.1	Classifier 3.2	Classifier 3.3
kNN	86.387	97.436	89.698
DT	68.775	69.354	72.283
SVM	80.299	94.040	87.143
DA	80.839	90.926	88.572
NB	83.862	92.262	86.115
ANN	97.500	100.00	99.167

Learning algorithm	F1Score (%)		
	Classifier 3.1	Classifier 3.2	Classifier 3.3
kNN	84.833	97.329	89.292
DT	67.705	68.699	72.253
SVM	79.018	93.545	86.624
DA	79.279	90.601	88.033
NB	80.706	91.963	85.413
ANN	97.895	100.00	99.167
Learning algorithm	Accuracy (%)		
	Classifier 3.1	Classifier 3.2	Classifier 3.3
kNN	83.333	97.222	88.889
DT	66.667	68.056	72.222
SVM	77.778	93.056	86.111
DA	77.778	90.278	87.500
NB	77.778	91.667	84.722
ANN	98.571	100.00	98.750

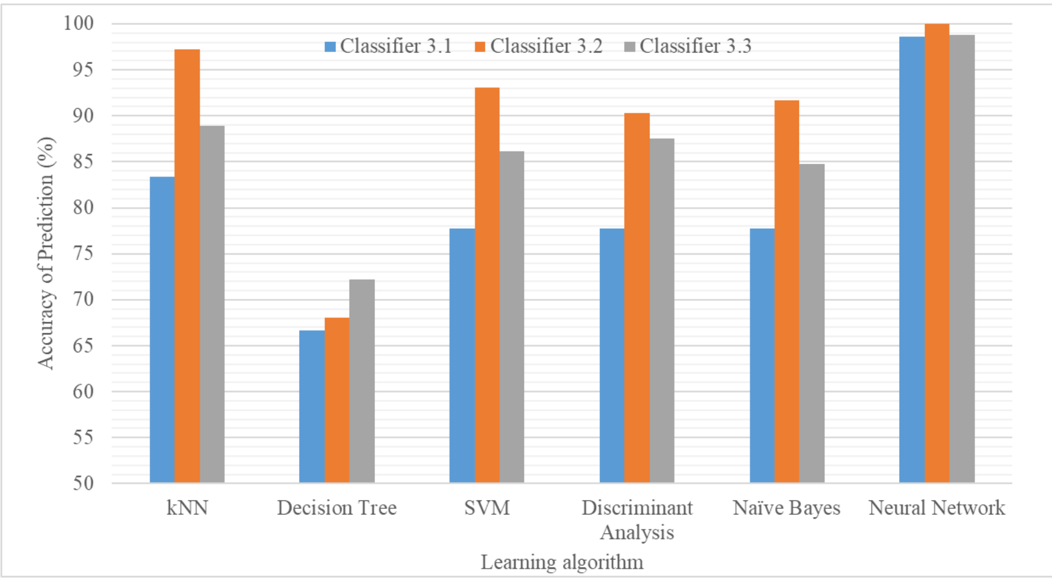


Figure 7.8 Accuracy of prediction for identification level 3

Consider the operation identification results for identification level 4 (Table. 7.4 to Table. 7.7 and Figure 7.9). For convenience, the performance parameters are displayed in separate tables. The summarised results are presented in Figure 7.9. There are 20 classifiers (Classifier 4.1 to Classifier 4.20) in this identification level. Only the best, the worst and the median results are displayed in the figure for clarity. The classifiers need to identify the construction stage at which the operation happens at this final identification level. The operations to be classified are essentially the same except for a minor difference in the stage of construction. This makes the identification tasks at this level extremely difficult. Achieving high performance seems to be highly challenging. However, ANN classifiers perform consistently well here. Except for Classifier 4.8 and Classifier 4.14, all other classifiers deliver accuracy and F1 Score of 100 per cent. The operations classified by these classifiers are observed to be related to support 6. This shows the dependency of the results on the data collected from that particular support. Considering the complexity of the identification problem, the accuracy is good enough and meets the purpose of identification. All other performance indices exhibit a similar pattern. kNN is observed to be the second-best learning algorithm based on overall performance. However, only 7 out of 20 classifiers delivered 100 per cent accuracy. The accuracy of the worst-performing classifier using kNN (Classifier 4.14 and Classifier 4.20) is as low as 75 per cent. The prediction results of other classifiers are not comparable. These results emphasise the significance of selecting the correct machine learning algorithm for operation identification.

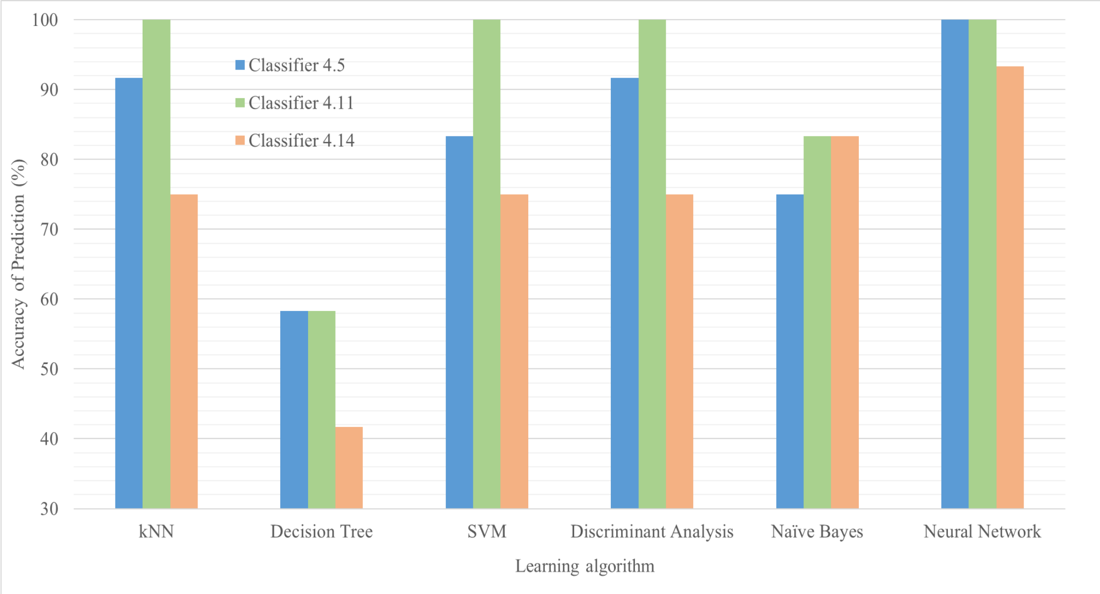


Figure 7.9 Accuracy of prediction for identification level 4

Table. 7.4 Accuracy of identification for identification level 4

Learning algorithm	Accuracy (%)				
	Classifier 4.1	Classifier 4.2	Classifier 4.3	Classifier 4.4	Classifier 4.5
kNN	100.00	94.444	91.667	91.667	91.667
DT	75.000	55.556	58.333	58.333	58.333
SVM	91.667	94.444	75.000	83.333	83.333
DA	91.667	94.444	75.000	83.333	91.667
NB	75.000	72.222	58.333	83.333	75.000
ANN	100.00	100.00	100.00	100.00	100.00
Learning algorithm	Classifier 4.6	Classifier 4.7	Classifier 4.8	Classifier 4.9	Classifier 4.10
kNN	91.667	83.333	91.667	100.00	100.00
DT	50.000	66.667	66.667	41.667	41.667
SVM	83.333	66.667	83.333	83.333	100.00
DA	75.000	75.000	75.000	91.667	91.667
NB	66.667	66.667	66.667	75.000	83.333
ANN	100.00	100.00	93.333	100.00	100.00

Learning algorithm	Classifier 4.11	Classifier 4.12	Classifier 4.13	Classifier 4.14	Classifier 4.15
kNN	100.00	91.667	91.667	75.000	83.333
DT	58.333	75.000	66.667	41.667	66.667
SVM	100.00	91.667	75.000	75.000	91.667
DA	100.00	91.667	100.00	75.000	100.00
NB	83.333	58.333	75.000	83.333	75.000
ANN	100.00	100.00	100.00	93.333	100.00
Learning algorithm	Classifier 4.16	Classifier 4.17	Classifier 4.18	Classifier 4.19	Classifier 4.20
kNN	100.00	100.00	100.00	91.667	75.000
DT	58.333	75.000	41.667	75.000	75.000
SVM	83.333	91.667	91.667	75.000	83.333
DA	83.333	100.00	83.333	91.667	83.333
NB	83.333	75.000	58.333	50.000	50.000
ANN	100.00	100.00	100.00	100.00	100.00

Table. 7.5 Precision for identification level 4

Learning algorithm	Precision (%)				
	Classifier 4.1	Classifier 4.2	Classifier 4.3	Classifier 4.4	Classifier 4.5
kNN	100.00	94.444	91.667	91.667	91.667
DT	75.000	55.556	58.333	58.333	58.333
SVM	91.667	94.444	75.000	83.333	83.333
DA	91.667	94.444	75.000	83.333	91.667
NB	75.000	72.222	58.333	83.333	75.000
ANN	100.00	100.00	100.00	100.00	100.00
Learning algorithm	Classifier 4.6	Classifier 4.7	Classifier 4.8	Classifier 4.9	Classifier 4.10
kNN	91.667	83.333	91.667	100.00	100.00
DT	50.000	66.667	66.667	41.667	41.667

SVM	83.333	66.667	83.333	83.333	100.00
DA	75.000	75.000	75.000	91.667	91.667
NB	66.667	66.667	66.667	75.000	83.333
ANN	100.00	100.00	90.000	100.00	100.00
Learning algorithm	Classifier 4.11	Classifier 4.12	Classifier 4.13	Classifier 4.14	Classifier 4.15
kNN	100.00	91.667	91.667	75.000	83.333
DT	58.333	75.000	66.667	41.667	66.667
SVM	100.00	91.667	75.000	75.000	91.667
DA	100.00	91.667	100.00	75.000	100.00
NB	83.333	58.333	75.000	83.333	75.000
ANN	100.00	100.00	100.00	95.000	100.00
Learning algorithm	Classifier 4.16	Classifier 4.17	Classifier 4.18	Classifier 4.19	Classifier 4.20
kNN	100.00	100.00	100.00	91.667	75.000
DT	58.333	75.000	41.667	75.000	75.000
SVM	83.333	91.667	91.667	75.000	83.333
DA	83.333	100.00	83.333	91.667	83.333
NB	83.333	75.000	58.333	50.000	50.000
ANN	100.00	100.00	100.00	100.00	100.00

Table. 7.6 Recall for identification level 4

Learning algorithm	Recall (%)				
	Classifier 4.1	Classifier 4.2	Classifier 4.3	Classifier 4.4	Classifier 4.5
kNN	100.00	95.238	92.857	92.857	92.857
DT	83.333	52.778	61.111	58.571	77.273
SVM	92.857	95.238	75.714	83.333	83.333
DA	92.857	95.238	75.714	83.333	92.857
NB	75.714	73.611	58.571	83.333	83.333
ANN	100.00	100.00	100.00	100.00	100.00

Learning algorithm	Classifier 4.6	Classifier 4.7	Classifier 4.8	Classifier 4.9	Classifier 4.10
kNN	92.857	83.333	92.857	100.00	100.00
DT	50.000	68.750	80.000	38.889	38.889
SVM	83.333	66.667	87.500	83.333	100.00
DA	75.714	75.714	75.714	92.857	92.857
NB	68.750	66.667	68.750	75.714	87.500
ANN	100.00	100.00	86.667	100.00	100.00
Learning algorithm	Classifier 4.11	Classifier 4.12	Classifier 4.13	Classifier 4.14	Classifier 4.15
kNN	100.00	92.857	92.857	75.714	87.500
DT	61.111	83.333	80.000	38.889	80.000
SVM	100.00	92.857	75.714	83.333	92.857
DA	100.00	92.857	100.00	75.714	100.00
NB	83.333	58.571	75.714	83.333	75.714
ANN	100.00	100.00	100.00	95.000	100.00
Learning algorithm	Classifier 4.16	Classifier 4.17	Classifier 4.18	Classifier 4.19	Classifier 4.20
kNN	100.00	100.00	100.00	92.857	75.714
DT	61.111	83.333	41.429	83.333	83.333
SVM	83.333	92.857	92.857	83.333	87.500
DA	87.500	100.00	83.333	92.857	87.500
NB	83.333	83.333	58.571	50.000	50.000
ANN	100.00	100.00	100.00	100.00	100.00

Table. 7.7 F1 Score for identification level 4

Learning algorithm	F1 Score (%)				
	Classifier 4.1	Classifier 4.2	Classifier 4.3	Classifier 4.4	Classifier 4.5
kNN	100.00	94.840	92.258	92.258	92.258
DT	78.947	54.131	59.690	58.452	66.480
SVM	92.258	94.840	75.355	83.333	83.333
DA	92.258	94.840	75.355	83.333	92.258

NB	75.355	72.910	58.452	83.333	78.947
ANN	100.00	100.00	100.00	100.00	100.00
Learning algorithm	Classifier 4.6	Classifier 4.7	Classifier 4.8	Classifier 4.9	Classifier 4.10
kNN	92.258	83.333	92.258	100.00	100.00
DT	50.000	67.692	72.727	40.230	40.230
SVM	83.333	66.667	85.366	83.333	100.00
DA	75.355	75.355	75.355	92.258	92.258
NB	67.692	66.667	67.692	75.355	85.366
ANN	100.00	100.00	88.000	100.00	100.00
Learning algorithm	Classifier 4.11	Classifier 4.12	Classifier 4.13	Classifier 4.14	Classifier 4.15
kNN	100.00	92.258	92.258	75.355	85.366
DT	59.690	78.947	72.727	40.230	72.727
SVM	100.00	92.258	75.355	78.947	92.258
DA	100.00	92.258	100.00	75.355	100.00
NB	83.333	58.452	75.355	83.333	75.355
ANN	100.00	100.00	100.00	95.000	100.00
Learning algorithm	Classifier 4.16	Classifier 4.17	Classifier 4.18	Classifier 4.19	Classifier 4.20
kNN	100.00	100.00	100.00	92.258	75.355
DT	59.690	78.947	41.547	78.947	78.947
SVM	83.333	92.258	92.258	78.947	85.366
DA	85.366	100.00	83.333	92.258	85.366
NB	83.333	78.947	58.452	50.000	50.000
ANN	100.00	100.00	100.00	100.00	100.00

In summary, ANN classifiers deliver the best performance in operation recognition at all identification levels. This shows that ANN can model the complex non-linear decision boundary that separates different operation classes. Other machine learning algorithms cannot easily model this relationship, or their learning strategies are not efficient enough to learn the correct relationship. Another interesting observation is that all ANN classifiers have simple network architecture. All classifiers possess only one hidden layer and, in most cases, the number of neurons is less than 10. Even for the most complex identification task, ANN has high accuracy. The accuracy obtained here is higher than what is reported in other operation recognition studies which used complex deep learning methods (Kim and Chi, 2019; Rashid and Louis, 2019; Roberts and Golparvar-Fard, 2019; Chen *et al.*, 2020; Slaton *et al.*, 2020). Irrespective of the complexity of the identification problem, conventional machine learning methods outperform complex identification methods with the right set of features, identification methodology and learning algorithm.

7.4.2 Performance of methodologies for operation identification

The performance of the hierarchical methodology for identification is compared with the conventional approach at different classification levels. The overall identification accuracy per classification level is shown in Figure 7.10. Precision, Recall, F1 Score and accuracy of classifiers and overall accuracy of the identification methodology per classification level are displayed in tabular form (Table 7.8 and Table 7.9).

Table 7.8 Performance parameters of conventional approach for identification

Classification level	Classifier	Precision (%)	Recall (%)	F1 Score (%)	Accuracy (%)
1	Classifier 1	95.00	94.79	94.89	99.58
2	Classifier 2	99.46	98.75	99.09	99.18
3	Classifier 3	95.75	94.50	95.11	95.92
4	Classifier 4	84.63	79.84	82.12	84.56

In the conventional approach for identification, the prediction accuracy is constantly decreasing with an increase in classification level. Hence, the finest level of classification has the least accuracy. This is due to the problem formulation in the conventional approach for identification. There is only one machine learning classifier per classification level. The number of classes in identification tasks from classification level 1 to 4 are 2, 5, 20 and 41. As the complexity of the identification task increases, the accuracy decreases. These results confirm the observations from previous studies (Akhavian and Behzadan, 2015). Other performance parameters such as precision, recall and F1 Score show similar trends. Even though classifier 2 shows slightly better performance than classifier 1, the decline continues with a higher number of classes. There is only a marginal difference between classifier 1 and 2 in terms of the number of classes. In contrast, the difference is substantially higher for classification level 3 and classification level 4. Hence declining performance becomes evident for these classification levels. The results show that the conventional approach is not suitable for developing an automated monitoring system.

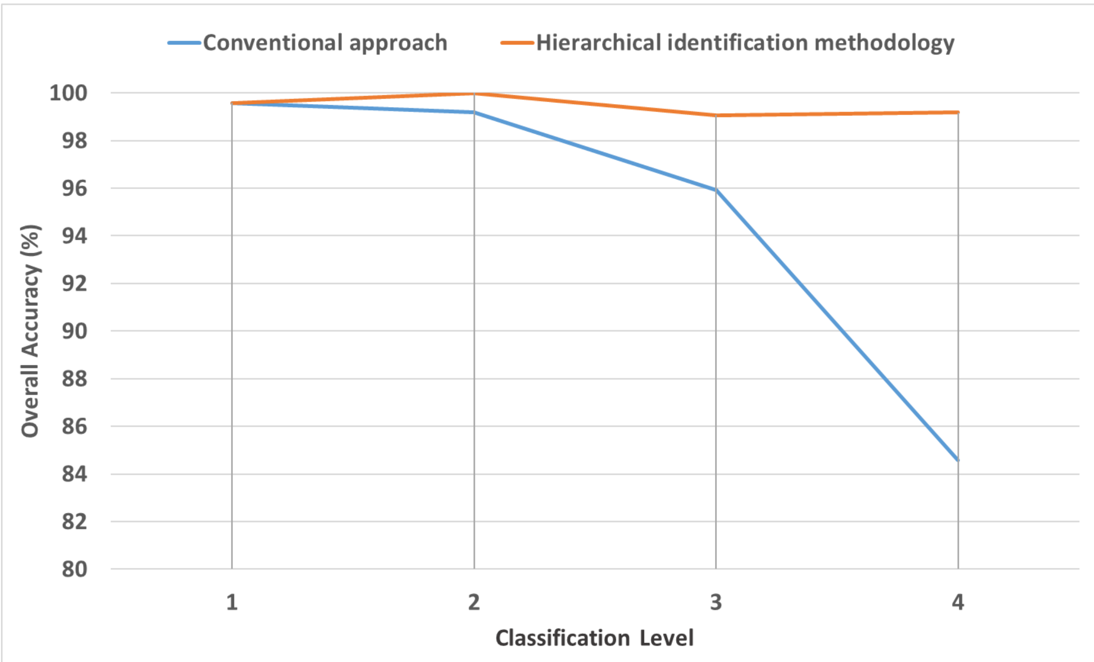


Figure 7.10 Performance comparison of conventional approach and hierarchical identification methodology

Table 7.9 Performance parameters of hierarchical identification methodology

Level of Classification	Classifier	Precision (%)	Recall (%)	F1 Score (%)	Accuracy (%)	Overall Accuracy per Classification Level (%)
1	Classifier 1.1	95.00	94.79	94.89	99.58	99.58
2	Classifier 2.1	100.00	100.00	100.00	100.00	100.00
3	Classifier 3.1	97.50	98.33	97.89	98.57	99.07
	Classifier 3.2	100.00	100.00	100.00	100.00	
	Classifier 3.3	99.17	99.17	99.17	98.75	
4	Classifier 4.1	100.00	100.00	100.00	100.00	99.19
	Classifier 4.2	100.00	100.00	100.00	100.00	
	Classifier 4.3	100.00	100.00	100.00	100.00	
	Classifier 4.4	100.00	100.00	100.00	100.00	
	Classifier 4.5	100.00	100.00	100.00	100.00	
	Classifier 4.6	100.00	100.00	100.00	100.00	
	Classifier 4.7	100.00	100.00	100.00	100.00	
	Classifier 4.8	90.00	86.67	88.00	93.33	
	Classifier 4.9	100.00	100.00	100.00	100.00	
	Classifier 4.10	100.00	100.00	100.00	100.00	
	Classifier 4.11	100.00	100.00	100.00	100.00	
	Classifier 4.12	100.00	100.00	100.00	100.00	
	Classifier 4.13	100.00	100.00	100.00	100.00	
	Classifier 4.14	95.00	95.00	95.00	93.33	
	Classifier 4.15	100.00	100.00	100.00	100.00	
	Classifier 4.16	100.00	100.00	100.00	100.00	
	Classifier 4.17	100.00	100.00	100.00	100.00	
	Classifier 4.18	100.00	100.00	100.00	100.00	
	Classifier 4.19	100.00	100.00	100.00	100.00	
	Classifier 4.20	100.00	100.00	100.00	100.00	

The performance of the hierarchical methodology is independent of the classification level. It depends mainly on the complexity of the identification task. The performance of the two identification methodologies was comparable in the initial classification levels. However, at the finer levels of classification, the hierarchical methodology outperforms the conventional approach with a significantly high level of accuracy. Hence, the hierarchical methodology is promising in delivering the high accuracy required for an automated monitoring system. The latter part of this section will discuss the performance of the classifiers in the hierarchical methodology in detail.

The classifiers in the hierarchical methodology consistently deliver the best prediction results, close to 100 per cent accuracy, except for two classifiers in classification level 4. The classifiers are composed of simple neural network architecture with one hidden layer, and the number of neurons in the hidden layer in most of the classifiers is less than 10. There are no studies on the identification of automated construction operations. However, the results can be compared with that of construction equipment activity identification. Kim et al. (J. Kim *et al.*, 2018) used vision-based activity identification methods incorporating the interactions between excavators and dump trucks to identify their activity with an accuracy of 91.27 per cent. Cheng et al. (Cheng *et al.*, 2017) used audio signals and SVM classifiers to identify construction equipment activities and obtained the best identification accuracy of over 90 per cent. Golparvar-Fard et al. (Golparvar-Fard *et al.*, 2013) used spatio-temporal features and SVM classifiers to identify activities of excavator and dump truck with 86.33 per cent and 98.33 per cent of accuracy, respectively. Akhavian and Behzadan (Akhavian and Behzadan, 2015) reported the highest accuracy of predicting the operations of a front-end loader using the neural network as 98.59 per cent. However, the prediction performance in that study decreased with finer levels of classification (86.09 per cent). The hierarchical methodology in the current research ensured consistently high performance from the highest level (99.58 per cent accuracy) to the finest classification level (99.19 per cent).

This was possible using a simple artificial neural network architecture, and no overfitting was observed, as indicated by the high prediction accuracy with unseen data. It is acknowledged that such high accuracy may not be achieved in real-world site conditions. However, the hierarchical methodology is still expected to have higher performance than the conventional approach because it takes advantage of the domain knowledge available in the form of decomposition of operations. The latest studies show reasonable identification performance with deep learning methods. It is frequently claimed that the major advantage of these methods is avoiding feature extraction. But the great challenge in implementing those methods include the generation of large datasets and high computational time. The feasibility deep learning for this identification task is explored in the subsequent sections. The current study followed a different approach to improve the performance of the existing methods, with an appropriate problem formulation based on domain knowledge.

There are 246 instances of idle and normal operation classes. All classifiers have an even class distribution, except for the first two classification levels. Hence the identification tasks at a particular classification level in the hierarchical methodology have relatively similar complexity. Figure 7.11 and Figure 7.12 show confusion matrices for selected classifiers. All these classifiers belong to the hierarchical methodology. In the confusion matrix, the actual class (target class) is represented by columns, whereas rows represent the predicted class (output class). The correctly classified data points are located on the main diagonal of the matrix, and misclassifications are on the off-diagonal positions. Each cell shows the fraction of data points that belong to that particular cell. In k-fold cross-validation, each fold generates a confusion matrix. The entries of each cell in the displayed confusion matrices are the average of corresponding values in all folds.

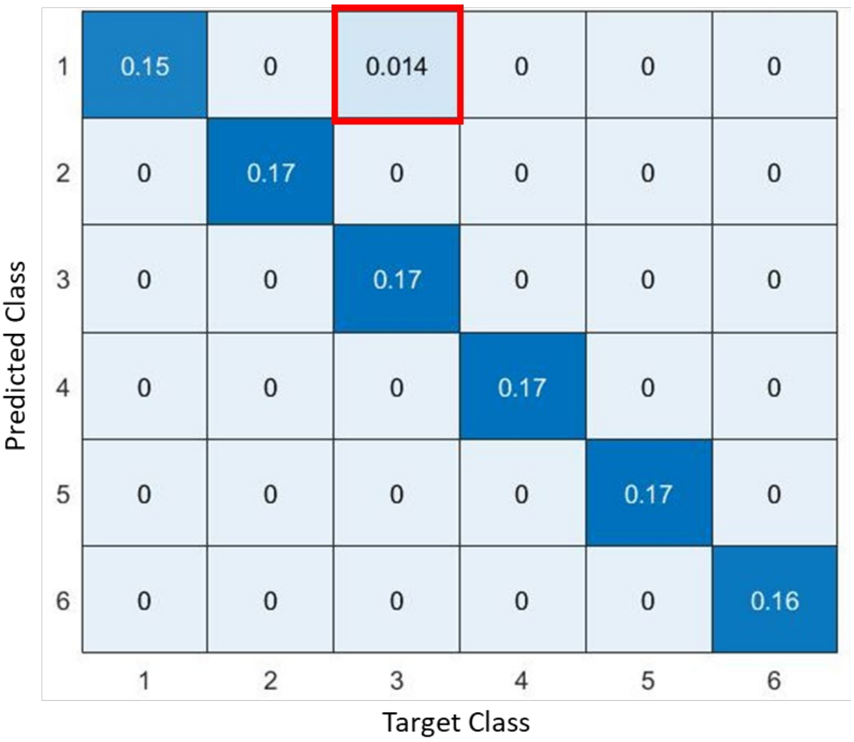


Figure 7.11 Confusion matrix for Classifier 3.1. The class labels 1, 2, …, 6 represent operation classes lowering support no.1, lowering support no.2, …, lowering support no.6 respectively.

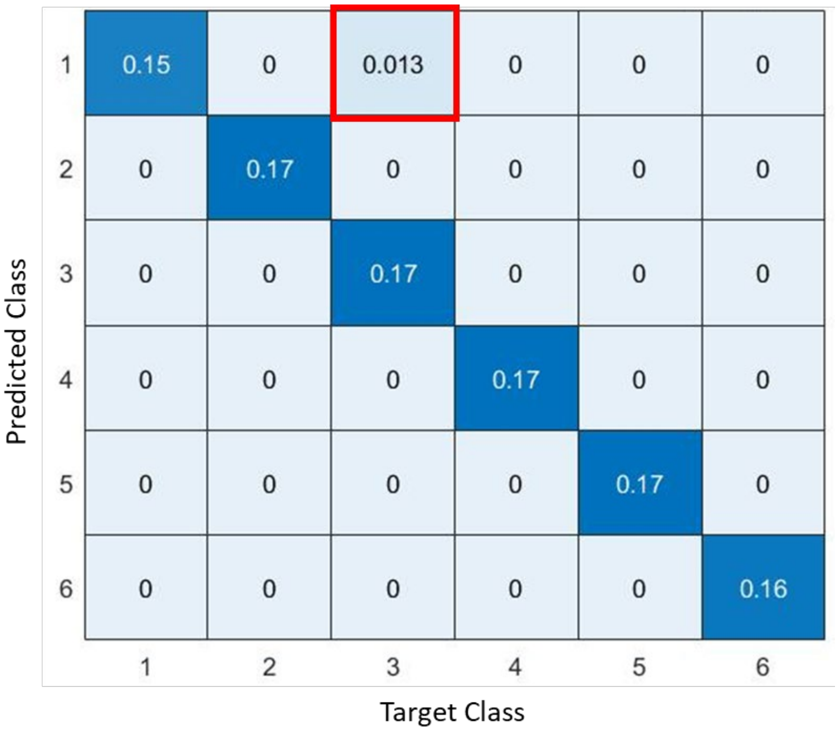


Figure 7.12 Confusion matrix for Classifier 3.3. The class labels 1, 2, …, 6 represent operation classes lifting support no.1, lifting support no.2, …, lifting support no.6 respectively.

Classifier 1.1 delivered good performance at classification level 1, even with unbalanced data sets. This confirms the ability of supervised learning classifiers to handle unbalanced data. However, the performance seems to be better with balanced classes. This justifies the superior performance of other classifiers compared to classifier 1.1. At classification level 3, classifiers 3.1 and classifier 3.3 have a minor dip in their performances. A closer look at the confusion matrices (Figure 7.11 and Figure 7.12) show the reason for this trend. The decline in performance is due to occasional misidentification of lowering or lifting operations at support three as similar operations at support one. Identification becomes more complex at classification level 4 due to the high similarity in classes. The classifiers at this level have to identify subtle changes in the patterns to recognise the stage of construction. However, most classifiers identified all instances accurately, except for classifier 4.8 and classifier 4.14. These classifiers correspond to operations' Lowering support no.6' and 'Connection of column module step6'. Since the number of instances is less in classification level 4, one misclassification reduces accuracy considerably. The classifiers in classification level 4 are 5-fold cross-validated due to the limited number of instances. This raises the question of the robustness of the classifiers. The following section discusses this issue in detail.

7.4.3 Noise tolerance of the classifiers

The data for the current study is acquired through controlled laboratory experiments. Data from the actual construction site may contain higher levels of noise. Once trained, the machine learning classifiers should identify the operations correctly even if the collected data contains noise. The generalisability and noise tolerance of the classifiers are tested by data containing noise. The raw acceleration signals are introduced with random noise whose maximum value ranges from 5 per cent to 50 per cent of the root mean square (RMS) of the signal. Totally six different sets of augmented data were created with varying percentage of noise. The features were extracted from the data sets supplied to all the trained neural network classifiers in the hierarchical methodology. The prediction results are given in Table 7.10 and Table 7.11.

Table 7.10 Prediction results for noisy data at classification level 1 to classification level 3

Noise content (%)	Prediction accuracy (%)				
	Classifier 1.1	Classifier 2.1	Classifier 3.1	Classifier 3.2	Classifier 3.3
5	99.60	100.00	100.00	100.00	100.00
10	99.20	100.00	100.00	100.00	95.80
20	97.60	99.10	100.00	100.00	97.20
30	95.90	97.00	95.80	97.20	95.80
40	95.50	88.90	88.90	93.10	93.10
50	95.10	76.10	76.40	86.10	90.30

Classifier 1.1 has a high tolerance for noisy data. The prediction accuracy is 95.1 per cent, even with 50 per cent of noise in the signal. It is interesting to note that the 10-fold cross-validation accuracy for this classifier was 99.58 per cent. Even a high percentage of error in the signal reduces the performance of the classifier slightly. Classifier 2.1 has a relatively high noise tolerance of up to 20 per cent. However, the performance of this classifier reduces considerably from 30 percentage onwards. A similar trend can be observed for classifier 3.1 and classifier 3.2. But the noise threshold for the drastic reduction in performance varies. Classifier 3.3 shows a consistent reduction in performance with an increase in noise. Classifier 3.1 and classifier 3.3 had 10-fold cross-validation accuracy of 98.57 per cent and 98.75 per cent, respectively. Nevertheless, these classifiers could identify operations with high accuracy up to a

certain percentage of noise. This shows the generalizability of the classifiers. The classifiers in classification level 4 show relatively high noise tolerance compared to all other classifiers. Some of the classifiers identified all operations correctly, even with 50 per cent of noise. These results evince the robustness of the classifiers. The noise threshold and the trend of decline in performance vary with the classifier.

Table 7.11 Prediction results for noisy data at classification level 4

Noise content (%)	Prediction accuracy (%)				
	Classifier 4.1	Classifier 4.2	Classifier 4.3	Classifier 4.4	Classifier 4.5
5	100.00	100.00	100.00	100.00	100.00
10	100.00	100.00	100.00	100.00	100.00
20	91.70	88.90	100.00	100.00	83.30
30	58.30	72.20	91.70	100.00	75.00
40	58.30	66.70	75.00	100.00	66.70
50	58.30	61.10	50.00	58.30	50.00
Noise content (%)	Classifier 4.6	Classifier 4.7	Classifier 4.8	Classifier 4.9	Classifier 4.10
5	100.00	100.00	91.70	100.00	100.00
10	100.00	91.70	91.70	100.00	100.00
20	91.70	83.30	91.70	100.00	100.00
30	83.30	58.30	91.70	100.00	100.00
40	83.30	58.30	91.70	91.70	100.00
50	83.30	50.00	83.30	100.00	100.00
Noise content (%)	Classifier 4.11	Classifier 4.12	Classifier 4.13	Classifier 4.14	Classifier 4.15
5	100.00	100.00	100.00	100.00	100.00
10	100.00	100.00	100.00	100.00	100.00
20	100.00	100.00	100.00	91.70	100.00
30	100.00	91.70	100.00	100.00	100.00
40	100.00	100.00	100.00	75.00	100.00

50	100.00	100.00	100.00	100.00	100.00
Noise content (%)	Classifier 4.16	Classifier 4.17	Classifier 4.18	Classifier 4.19	Classifier 4.20
5	100.00	100.00	100.00	100.00	100.00
10	100.00	100.00	100.00	100.00	83.30
20	100.00	100.00	100.00	100.00	91.70
30	91.70	100.00	91.70	100.00	83.30
40	58.30	91.70	100.00	91.70	83.30
50	100.00	100.00	100.00	100.00	100.00

7.4.4 Performance of deep learning classifiers in operation identification

The current section presents the performance of deep learning classifiers in identifying major operation classes in an automated construction. The deep learning classifiers are trained using different types of augmented datasets and named DL1, DL2, …, DL5. These classifiers are Bidirectional Long Short-Term Memory (Bi-LSTM) networks that learn sequential information from both ends of the time series. The number of instances in datasets for training, validation, and testing is 4176, 840 and 840. The four major automated construction activities - connection of column module, coordinated lifting, lifting support and lowering support - were identified. The original data points in the 'coordinated lifting' class are slightly lesser than that of the other classes. Each augmentation method is combined with oversampling to balance the number of data points across the classes. This ensured unbiased learning. The raw accelerometer measurements taken from eight locations on the structure were supplied as input data. Since the duration of each operation varies, the length of the input signal also varies. The raw data is truncated to a maximum size of 500 timesteps with a moving widow size of 100 timesteps to reduce the overall training time. All of the classifiers were trained in a GPU environment (GeForce RTX 2060). The overall experiments to select the best deep learning classifier for a specific dataset takes several days to complete.

However, the testing is faster once the hyperparameters for the best classifier were identified. Therefore, the actual implementation of an identification method based on kinematic data is much more feasible than computer vision-based methods.

Table 7.12 Hyperparameters of the deep learning classifiers

Classifier	Augmentation methods	Number of hidden units	Number of iterations	Maximum epochs	Minibatch size	Learning rate
DL1	Over sampling	100	569	3	22	0.0007
DL2	Jittering and over sampling	100	1392	8	24	0.0009
DL3	Scaling and over sampling	100	895	6	28	0.007
DL4	Down sampling and over sampling	100	2088	9	18	0.0037
DL5	Jittering, scaling, down sampling and over sampling	100	1566	9	24	0.0008

Table 7.12 displays the hyperparameters of the best classifiers in each category. The optimal minibatch size of the classifiers ranges from 18 to 28, and the learning rate ranges from 0.0007 to 0.007. The analysis results were summarised in Table 7.13 and Table 7.14. Classifiers DL1 to DL4 use datasets predominantly generated by a single augmentation method. In contrast, DL5 is trained by a dataset generated as a result of all the four data augmentation methods. The machine learning classifiers are numbered from ML1 to ML6; each uses a specific learning algorithm. DL1 trained on oversampled dataset delivered the best performance among the deep learning classifiers, with 96.43 per cent accuracy and 96.65 per cent F1 score. Conversely, traditional machine learning classifier ML6 based on ANN secures 100 per cent accuracy and F1 Score.

Table 7.13 Results of deep learning classification for operation identification

DL Classifier	Augmentation methods	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
DL1	Over sampling	96.43	96.88	96.43	96.65
DL2	Jittering and over sampling	91.43	92.23	91.43	91.83
DL3	Scaling and over sampling	77.86	81.97	77.86	79.86
DL4	Down sampling and over sampling	92.14	93.15	92.14	92.64
DL5	Jittering, scaling, down sampling and over sampling	84.76	85.37	84.76	85.07

Table 7.14 Results of machine learning classification for operation identification

ML Classifier	Learning algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1 Score (%)
ML1	kNN	93.16	94.55	94.44	94.50
ML2	DT	94.87	94.78	94.79	94.79
ML3	SVM	97.86	97.31	98.26	97.78
ML4	DA	96.58	97.41	97.22	97.31
ML5	NB	92.74	94.23	92.01	93.11
ML6	ANN	100.00	100.00	100.00	100.00

Notes: kNN = k-Nearest Neighbour; DT = Decision Tree; SVM = Support Vector Machines;
DA = Discriminant Analysis; NB = Naïve Bayes; ANN = Artificial Neural Network.

Deep learning techniques may deliver superior performance in activity recognition under certain condition. However, the technique for activity recognition has to be selected carefully after considering several important factors. The availability of a large quantum of training data is one of the essential prerequisites. Data augmentation methods are often used to overcome this issue. However, the lack of variety in the original dataset may greatly affects the performance of the classifier. This may often result in overfitting. In this scenario, conventional machine learning methods offer a better solution. Consider Table 7.13, which compares the best two classifiers from machine learning and deep learning classification. The best performing classifier ML6 is an artificial neural network with a simple architecture. The second-best classifier is an SVM with a polynomial kernel. None of the deep learning classifiers presented here could match the performance of the conventional machine learning classifiers.

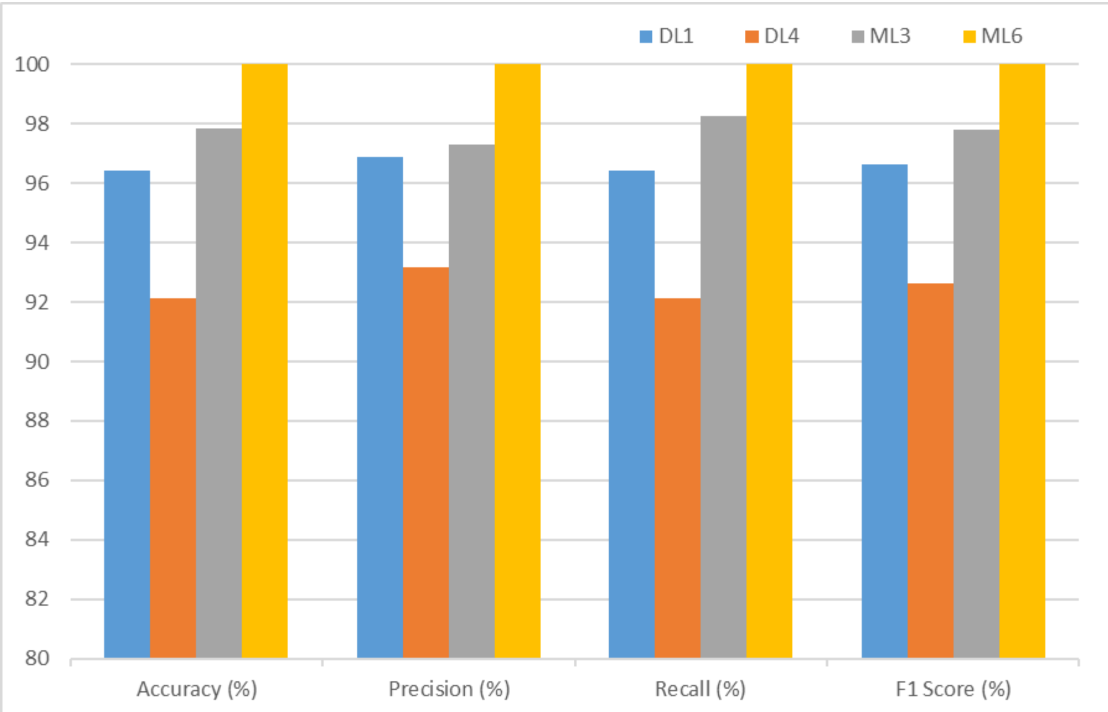


Figure 7.13 Comparison of the best two classifiers from machine learning and deep learning classification

Some of the previous studies used complex or hybrid deep learning classifiers for construction equipment activity recognition. The comparison of activity identification performances of these methods and that of the current study is given in Table 7.15. These results show that the complexity of the learning algorithm may not ensure better performance. The time, cost, and efforts to collect good quality data and the development of a complex classifier must be justified by its performance in the application domain. Ensuring the best performance of deep learning algorithms require in-depth knowledge of the network architecture. The scarcity of in-house deep learning experts in the construction engineering domain makes the actual implementation of these techniques expensive(Akinosho *et al.*, 2020). Without the additional cost of collecting a large quantum of data or augmentation or huge training time, the conventional machine learning classifiers delivered better results. The current study also shows the capability of conventional machine learning classifiers in activity recognition for a sparsely explored application domain.

Table 7.15 Comparison of activity identification performance

Study	Equipment	Data collected	Number of activity classes	Methods/ Algorithms	Performance in activity identification
(Luo *et al.*, 2018)	Worker and various equipment	Images	17	Faster R-CNN + ResNet-50, Relevance Networks	Precision: 62.4 % Recall: 87.3 %
(Kim *et al.*, 2019)	Excavator	Images	4	TLD, Hybrid network (CNN and LSTM)	Average accuracy: 93.8 %
(Roberts and Golparvar-Fard, 2019)	Excavator and dump truck	Videos	Excavator: 5 Dump truck: 2	CNN (ResNeXt-101), HMM, GMM, SVM	Accuracy for excavators: 86.8 %, for dump trucks: 88.5 %
(Chen *et al.*, 2020)	Excavators	Videos	3	Faster R-CNN	Overall accuracy 87.6%
(Rashid and Louis, 2019)	Excavator and front-end loader	IMU data	Excavator: 9 Front-end loader: 10	LSTM	Accuracy for excavator: 97.9 %, for front-end loader:

					96.7 %. F1 Score for excavator: 97.6 % for front-end loader 96.3 %.
(Slaton *et al.*, 2020)	Roller compactor and excavator	Acceleration data	Roller compactor: 6 Excavator: 7	Hybrid network (CNN and LSTM)	Accuracy for compactor: 77.1 %, for excavator: 77.6 %.
Current study	ACS	Acceleration data	4	LSTM	Accuracy: 96.43 % Precision: 96.88 % Recall: 96.43 % F1 Score: 96.65 %
Current study	ACS	Acceleration data	4	ANN	Accuracy: 100 % Precision: 100 % Recall: 100 % F1 Score: 100 %

Notes: CNN = Convolutional Neural Network; TDL= Tracking-Learning-Detection; LSTM = Long Short-Term Memory Network; HMM = Hidden Markov Model; GMM = Gaussian Mixture Model; SVM = Support Vector Machines; ACS = Automated Construction System; ANN = Artificial Neural Network.

The ANN model for predicting the major operation classes delivered 100 per cent in all performance measures. This does not imply that this model will consistently deliver correct predictions. It indicates that the model delivers high performance for the current dataset and potentially identifies future operations with high accuracy compared to other classifiers in a similar context. It is normal to have a high performing machine learning model. An example of one of such high performing models developed by Laguarta *et al.* from MIT AutoID Laboratory is presented here (Laguarta *et al.*, 2020). The performance of the prediction model may often decline during implementation.

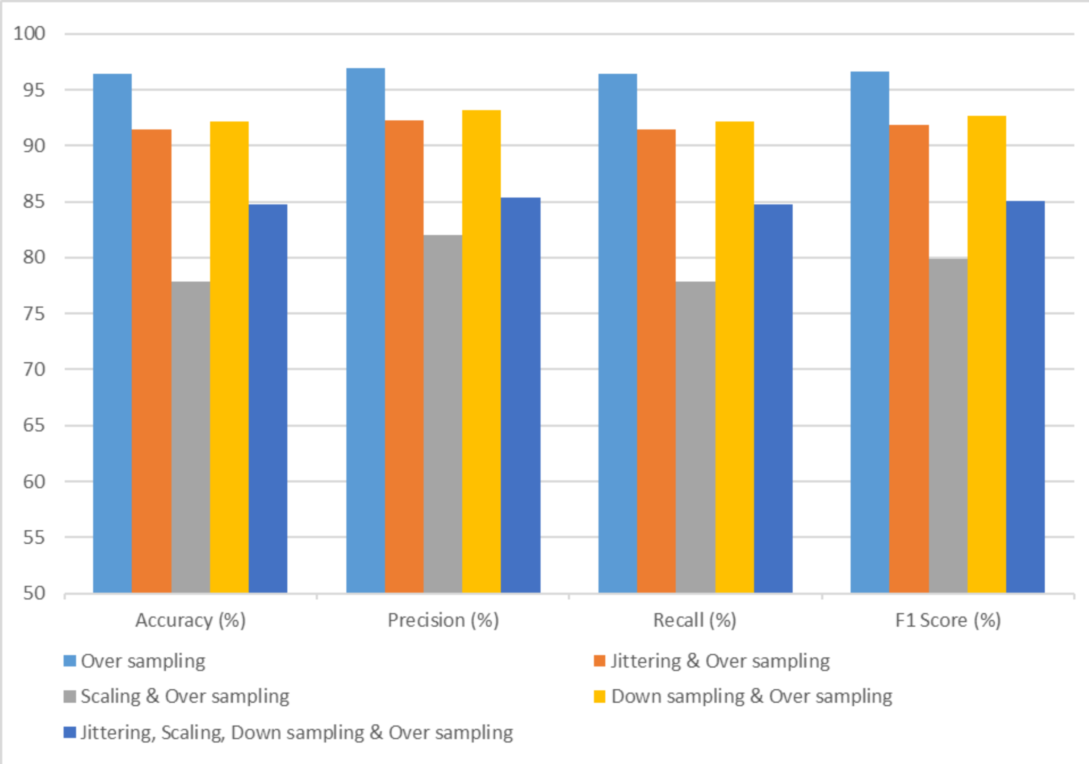


Figure 7.14 Effect of data augmentation techniques on deep learning classification

The need to select relevant handcrafted features is considered one of the major drawbacks of conventional machine learning techniques. The introduction of deep learning may avoid the feature selection step. However, domain knowledge is necessary to develop a robust classifier for activity recognition. Consider Figure 7.14, which shows the influence of the data augmentation techniques on the performance of the classifiers. All of the augmentation methods except scaling result in classifiers with more than 91 per cent accuracy and F1 Score. The accuracy drops as low as 77.86 per cent while using scaling for data augmentation. Intuitively, the introduction of a variety of data augmentation methods should enhance the performance of a classifier. However, the classifier DL5, which uses all of the data augmentation methods, is among the worst-performing classifiers. This might be due to the presence of a scaled dataset. Hence, it can be inferred that the amplitude of the time-series data plays a significant role in distinguishing the classes. These findings can also be confirmed by visual inspection of the measured data. Therefore, the data augmentation methods have to be carefully selected so that they should not affect the characteristics of the original dataset.

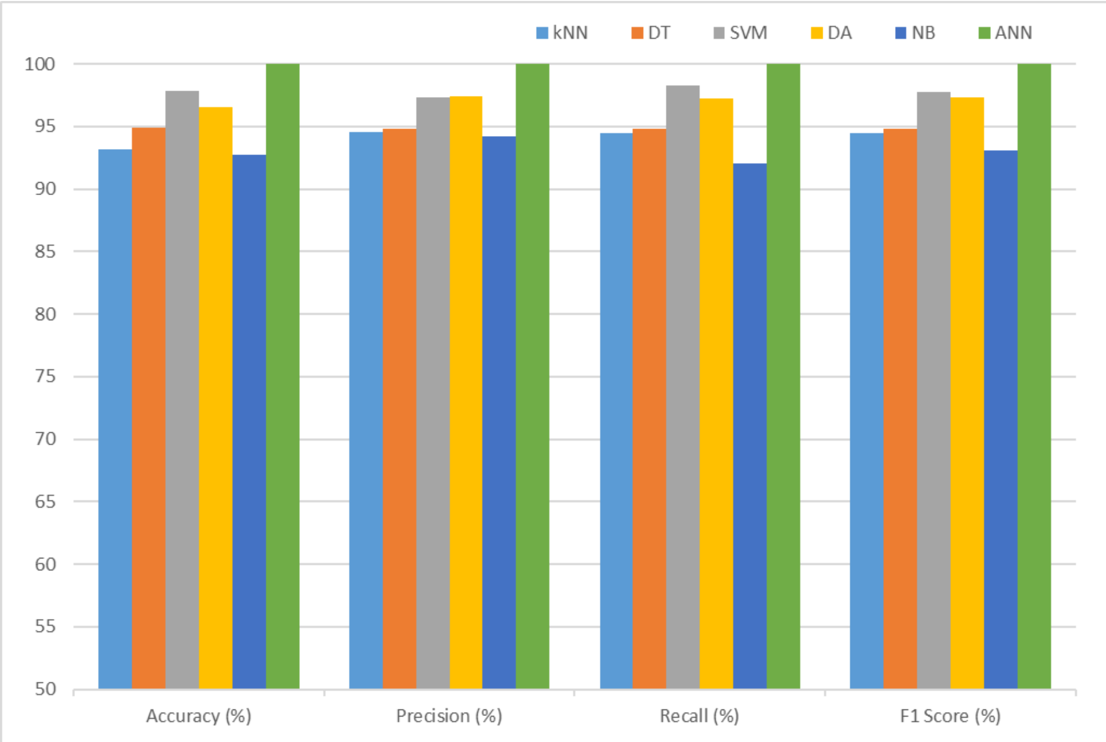


Figure 7.15 Performance matrices of machine learning classifiers

All machine learning classifiers in this study perform at par with or better than deep learning classifiers (Figure 7.13). In addition to five time-domain features, five frequency domain features were also used for training these classifiers. Deep learning classifiers can learn the statistical features from the time series data. However, it cannot directly learn the frequency domain features from the input data. Activity recognition problems that involve operations with signature vibration or frequency require classifiers trained with frequency-domain features. Deep learning classifiers trained with limited time-domain data may be inadequate for these problems. Hence, further studies on the identification of automated construction activities were conducted using the best performing machine learning classifier, ANN.

7.5 ILLUSTRATION OF THE GENERALIZABILITY OF THE OPERATION IDENTIFICATION METHODOLOGY

The hierarchical identification methodology proposed in this study is generic and can be potentially applied to several operation recognition tasks in construction. This section illustrates the generalizability of the proposed methodology with an example of an excavator operation identification. The operations described in this example is adapted from (Akhavian and Behzadan, 2015). An excavator is commonly used for earth excavation, and moving works on construction sites. The fundamental idea of the hierarchical methodology is exploring the subclasses of a previously identified operation class for more details. Hence, the first step is developing a schema containing the equipment states, operations, and hierarchical relationships. This step helps to determine the maximum classification levels for the particular equipment. A possible operation decomposition for excavator operations is shown in Figure 7.16. In this example, all operations of an excavator can be identified within four classification levels if we include the states 'Engine off' and 'Engine on' in the hierarchy. Development of the schema helps to enumerate the operation classes to be identified. In Figure 7.16, white boxes represent the operation classes or states, and yellow boxes represent the classification levels.

The next step is identifying the purpose and level of details required for operation recognition. If the purpose is to estimate the cycle time for simulation input modelling, a high level of operation details is required (Akhavian and Behzadan, 2015). This means that the operations have to be identified up to classification level 4, in which all sub-operations are recognised. If the purpose is to identify the overall productivity of the equipment, information up to classification level 3 is sufficient to recognise major operation classes (Kim and Chi, 2019). Classification level 2 is sufficient for estimating the emission rate for sustainability analysis. How much time the engine is turned on in the idle condition gives an estimate of wasteful emission. Fuel consumption can be estimated from classification level 1 itself.

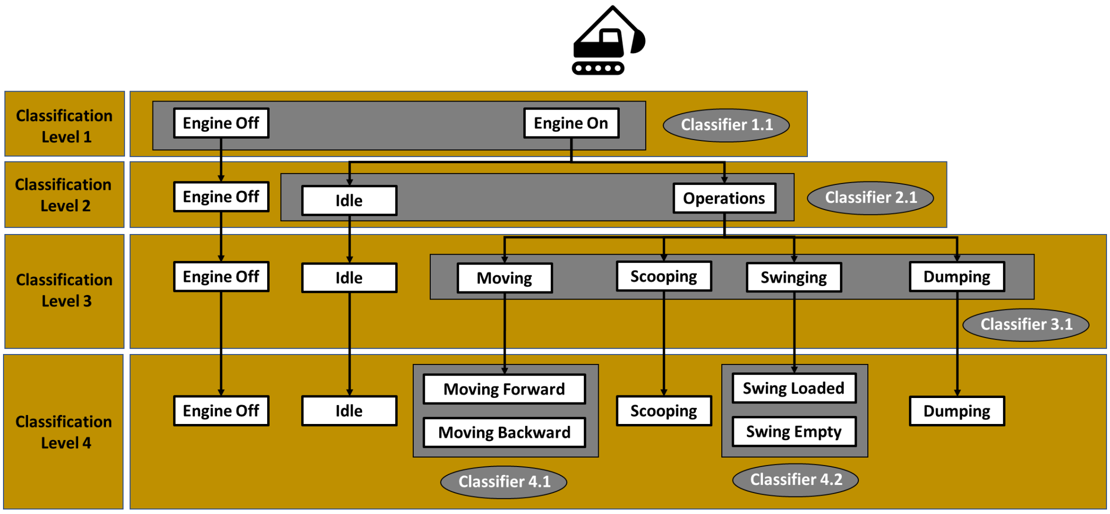


Figure 7.16 Hierarchical methodology for identification of operations or states of an excavator

The next step is to identify the machine learning classifiers that separate the operation classes. In general, a classifier is chosen at each level for separating a particular operation (or state) further. This is the fundamental difference between the hierarchical methodology and the conventional approach. In the conventional approach, a single machine learning classifier separates the data into all the operation classes. For example, in (Akhavian and Behzadan, 2015), one machine learning classifier is used to separate operation into five classes. The classes were represented as a flat list of output nodes of a neural network. In contrast, multiple classifiers are trained in the hierarchical methodology to separate the classes, one after another in a cascading network. The classifiers are represented in Figure 7.16. by grey boxes, which contain the classes identified by them. These classifiers are named as shown in the grey ovals next to them. For example, classifier 1.1 is assigned to identify 'Engine off' and 'Engine on' states at classification level 1. If the engine is turned off, there is no need for further classification. If the engine is turned on, further classification is needed to identify the subclasses of that state. Similarly, subclasses of a previously identified operation will be further separated at subsequent classification levels, and classifiers will be assigned accordingly. Unlike ACS, the excavator has a relatively simple hierarchy of operations. Only at classification level 4, there is more than one classifier. The ACS contains larger combinations of operations and states. Thus, the classification problem is highly complex. The current identification methodology presents a novel problem formulation that enhances the robustness of identification. Activity recognition in automated construction is a novel and challenging application that has not been discussed in the published literature. Activity recognition with high accuracy and a high level of details is essential for monitoring the ACS. Hence, a new methodology is developed for meeting these requirements. With four classification levels, we can obtain sufficient details that are necessary to take corrective actions. However, based on the complexity level of operations to be identified in a piece of construction equipment, the number of classification levels could vary.

Since the primary application area of this research is automated construction, a more detailed discussion of the application of the methodology to other construction operations is not attempted here. The case of the excavator is presented purely for illustrating the generalizability of the approach. The particular hierarchical representation of the excavator operations is provided as an example. The sub-operations could be modified based on the purpose of identification.

7.6 CONCLUSIONS

This chapter presents the selection of appropriate methodologies and algorithms for recognising automated construction operations. The conventional approach adopted in all the previous operation recognition studies uses a single machine learning classifier that separates all the operations classes. The newly developed hierarchical methodology does not use a flat list of classes like the conventional approach. Instead, it utilises the hierarchical relationship between operations to decompose them into various classification levels. Multiple hierarchically organised machine learning classifiers address the identification problem at each classification level. Six different machine learning algorithms were tested for each classifier. These two methodologies were evaluated for their efficiency in identifying the operations of an automated construction system prototype. Besides, the potential of deep learning classifiers in identifying major automated construction operations was explored using LSTM networks. Five deep learning classifiers were trained with different datasets. Each dataset is generated by a combination of four different data augmentation methods. The performance of the deep learning classifiers was compared with that of the conventional machine learning classifiers. The machine learning classifiers were trained using the features selected from the original dataset, and deep learning classifiers with augmented datasets.

1. The structure of the problem formulation in the hierarchical operation identification methodology ensures consistent performance irrespective of the complexity of the problem. In contrast, the performance of the conventional operation identification approach drops with the increase in complexity. The performances of the two identification methodologies were comparable at the initial classification levels. However, at finer classification levels, the hierarchical methodology outperformed the conventional approach with 3 to 15 per cent higher accuracy. Even though both identification methodologies used the same machine learning algorithm and datasets, the formulation of the identification problem made a tremendous difference in their performances. This study emphasises the

significance of problem formulation for operation identification. The hierarchical organisation of classes incorporates domain knowledge that helps the machine learning algorithm separate operations more efficiently.

2. The neural network classifiers with a simple architecture consistently delivered a high performance at all classification levels of the hierarchical methodology. This study also confirms the efficiency of neural network classifiers for equipment operation identification from sensor data. The generalisability and noise tolerance of these classifiers demonstrate the prospect of using them to develop an automated construction monitoring system.

3. If the quantity of unique datasets is limited, data augmentation may not improve the performance of deep learning classifiers. Therefore, all of the conventional machine learning classifiers performed equivalently or better than LSTM classifiers in the current study. It can also be inferred that complex learning algorithms need not necessarily result in better performance. The best performing classifier in this study is an artificial neural network with 100 per cent accuracy. The second-best classifier is an SVM with a polynomial kernel which delivered an accuracy of 97.86 per cent. In contrast, the best performing deep learning classifier secured an accuracy of 96.43 per cent.

4. Augmenting data may not deliver better results if it alters the characteristics of the original dataset. All of the augmentation methods, except scaling, result in classifiers with more than 91 per cent accuracy and F1 score. While using scaling for data augmentation, the accuracy drops as low as 77.86 per cent. Intuitively, the introduction of a variety of data augmentation methods should enhance the performance of a classifier. However, the classifier that uses all of the data

augmentation methods is among the worst-performing classifiers. This is mainly because of the presence of the scaled dataset. Domain knowledge is necessary to develop a robust classifier for activity recognition, even with deep learning. The introduction of deep learning may avoid feature selection. However, the selection of appropriate data augmentation methods and the design of network architecture demands greater expertise.

5. LSTM classifiers trained with limited time-domain data may be inadequate for vibration-based activity recognition. Activity recognition problems that involve operations with signature vibration or frequency require classifiers that trained with frequency-domain features. LSTM classifiers learn the statistical features from the time series data. However, learning the frequency domain features directly from the input data may be challenging.

6. The classifiers for equipment activity recognition must be selected based on the identification problem and availability of datasets. Implementation of traditional machine learning for construction activity recognition is more feasible than that of deep learning. The actual implementation of deep learning methods in the construction industry demands high investment in terms of time, cost, and efforts to collect good quality data in addition to high training time and computational power. In contrast, simple machine learning algorithms with hand-crafted features may offer better performance compared to complex algorithms.

CHAPTER 8

ANALYSIS AND RESULTS: HUS-ML FRAMEWORK FOR OPERATION IDENTIFICATION AND FAULT DETECTION

8.1 INTRODUCTION

The introduction of automation in construction alleviates some of the safety concerns in conventional construction. However, it presents another set of intricate scenarios involving the machines and the workers. Automated construction is faster than conventional construction. Hence, undetected faults in any operation could escalate into a serious accident in a short time (Harichandran et al., 2020a). Therefore, automated monitoring is a necessary requirement for the safe implementation of automation in construction.

The main operator of an Automated Construction System (ACS) controls the operations from a remote location. The automated monitoring system should provide real-time information about ongoing construction. In the ideal scenario, the monitoring system should detect any early signs of faults in the ongoing operation and warn the operator about the impending condition. This warning enables the operator to take proper corrective measures to mitigate accidents or construction failures. Therefore, the crucial steps in construction monitoring are activity recognition and fault detection.

Even though current methods have achieved reasonably good accuracy in identifying construction activities (Roberts and Golparvar-Fard, 2019; Slaton et al., 2020), most of these methods identify only high-level activities with minimum details. The reason for the earlier focus on macro-level activities is that the purpose of identification did not require low-level details. The primary purposes of earlier work were computation of cycle time of operations; estimation of fuel consumption, emission rate or productivity of equipment; assessment of equipment condition, and construction progress monitoring (Harichandran et al., 2018; Kim and Chi, 2019; Chen et al., 2020). In contrast, a high level of details about the activities is necessary to take appropriate control actions to avoid accidents. The complexity of interaction between labour and machine is higher in automated construction than in conventional construction. Therefore, equipment fault detection is of paramount importance. The existing fault detection studies on construction equipment are limited to excavators, dump trucks, and tower cranes (Radlov and Ivanov, 2020; Lin et al., 2021). Most of these studies do not offer a systematic method for the early detection of faulty operations. Besides, issues such as the paucity of data related to faulty operations have been overlooked.

The objective of this study is to develop a robust method for activity recognition and early fault detection in automated construction. A new framework called Hybrid Unsupervised and Supervised Machine Learning (HUS-ML) has been developed in this work. The details of the framework and its advantages are explained in this chapter. The HUS-ML framework identifies the faulty operations with limited data. Faulty conditions in machines are unpredictable, and the availability of faulty data is often limited (Matzka, 2020b). Therefore, it is a desirable quality for a monitoring framework to predict faulty conditions with limited data.

The HUS-ML framework detects early signs of failure during automated construction. The early signs refer to the 'early signs' in the pattern of the sensing data that indicates deviation from normal operations. This data corresponding to the anomalous pattern ('early signs') is further analysed using the HUS-ML algorithm to extract more information about the faulty condition. Based on the available information on the type and location of the fault, the operator can take appropriate corrective actions.

The proposed framework is tested on a prototype of an ACS for low-rise building construction. The acceleration data from the structure is supplied as the input. A hierarchical arrangement of the identification problems extracts a high level of operation details. Supervised learning and unsupervised learning ensure accurate identification of normal operations and faulty condition. The HUS-ML framework is also validated on an independent predictive maintenance dataset.

The remaining sections are arranged as follows. The implementation and validation of the HUS-ML framework are described in section 8.2 with a detailed description of the training and testing phase. Section 8.3 presents the results and discussion. The validation of the proposed framework on a benchmark dataset is presented in section 8.4. Finally, section 8.5 concludes the chapter with significant outcomes of the study.

8.2 VALIDATION OF THE HUS-ML FRAMEWORK

The HUS-ML framework is validated and evaluated using the prototype of an Automated Construction System (ACS) under laboratory conditions. Consider the overall HUS-ML methodology illustrated in Figure 8.1. The controlled experiments at step 1 and actual automated construction at step 7 were performed by an ACS prototype developed at the Building Automation Laboratory, IIT Madras (Harichandran et al., 2019a, 2019b, 2020b, 2020a). HBM universal measuring amplifier QuantumX MX840B was deployed to collect acceleration data from the structure under construction. Step 2 and preliminary stages of step 3 were carried out by HBM data acquisition software CATMAN (HBM, 2020). The ground truth labels and timestamps of the operations were manually entered in macro-enabled Microsoft Excel sheets. The later stages of data pre-processing (step 3), HUS-ML analysis, and model generation (steps 4 to 6 and 8) were performed in MATLAB.

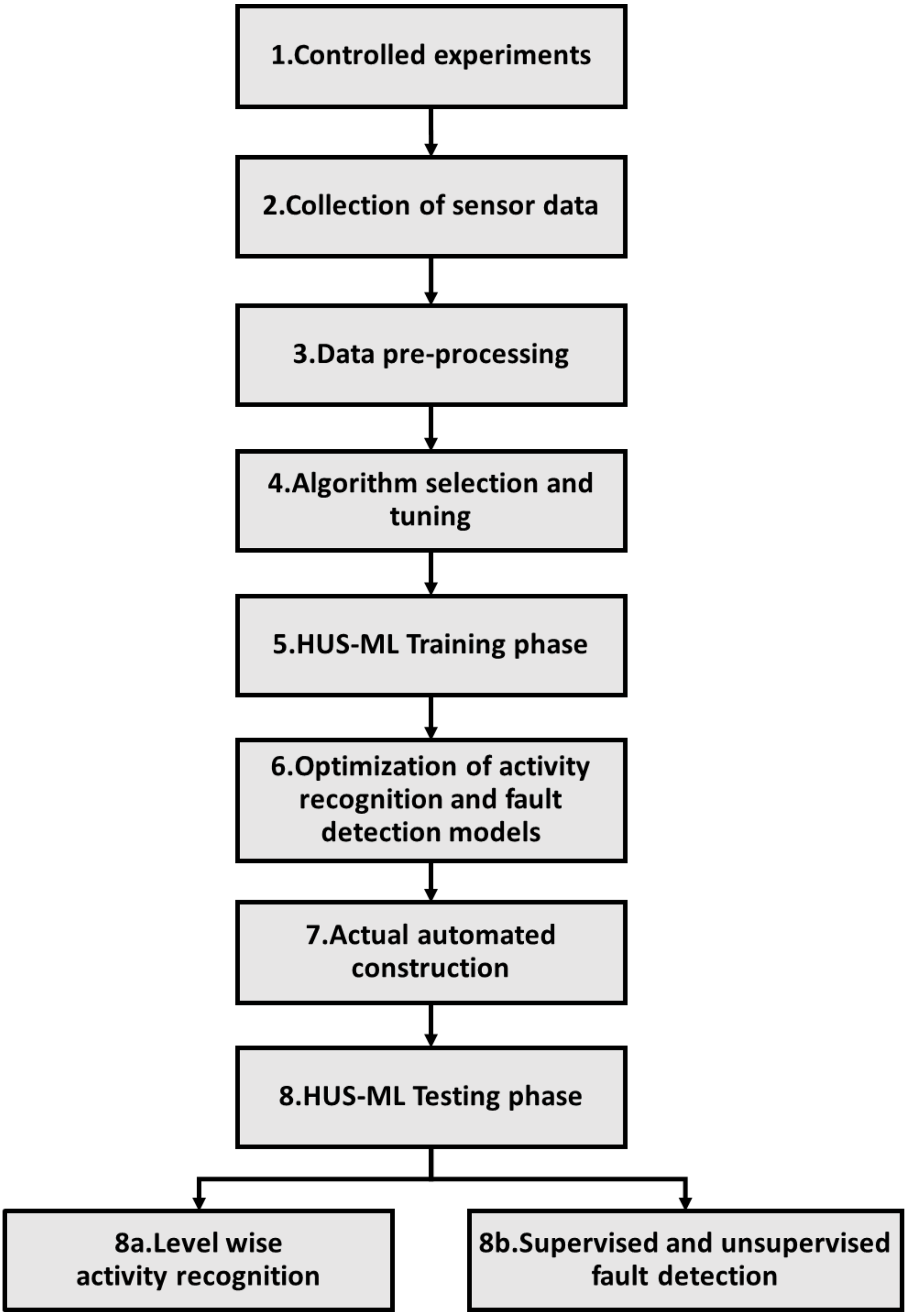


Figure 8.1 Overview of operation identification and fault detection by HUS-ML

Each iteration of an experiment contains two cycles of automated top-down construction (Harichandran *et al.*, 2020b). The two operation cycles were performed to cover all major categories and subcategories of automated construction. Accelerometers were deployed at key locations on the structure. The vibration (acceleration) measurements during operations were collected through data acquisition systems. The measured acceleration data and corresponding timestamps were visualised in CATMAN. This information is compared with timestamps in the Excel logbook to generate a ground truth label for each operation. The labelled datasets were then imported into MATLAB for further cleaning, feature extraction, feature scaling, and splitting.

8.2.1 HUS-ML training phase

HUS-ML training at each identification level comprises supervised learning and unsupervised learning. Supervised learning models are trained to recognise actual operations or faulty operations from the given classes (known classes). Unsupervised learning models detect unforeseen faulty operations based on Gaussian models. An overview of the training phase of the HUS-ML framework is presented in Section 4.3.1. Each step of the HUS-ML training for the ACS is described in detail in this section.

8.2.1.1 Hierarchical activity decomposition and assigning classification models

In the first identification level, the input data is identified as 'Idle' or 'Operations.' The second level divides the 'Operations' into major operation classes and associated failure classes. The current ACS has four major operation classes, viz. 'Connection of column module,' 'Coordinated lifting,' 'Lifting support,' and 'Lowering support'; and one faulty operation class viz. 'Support moving faster during Coordinated lifting.' Therefore, the 'Operations' class is divided into five subclasses at identification level 2. At identification level 3, the previously identified operation class is further divided into sub-operation categories based on the location or construction step.

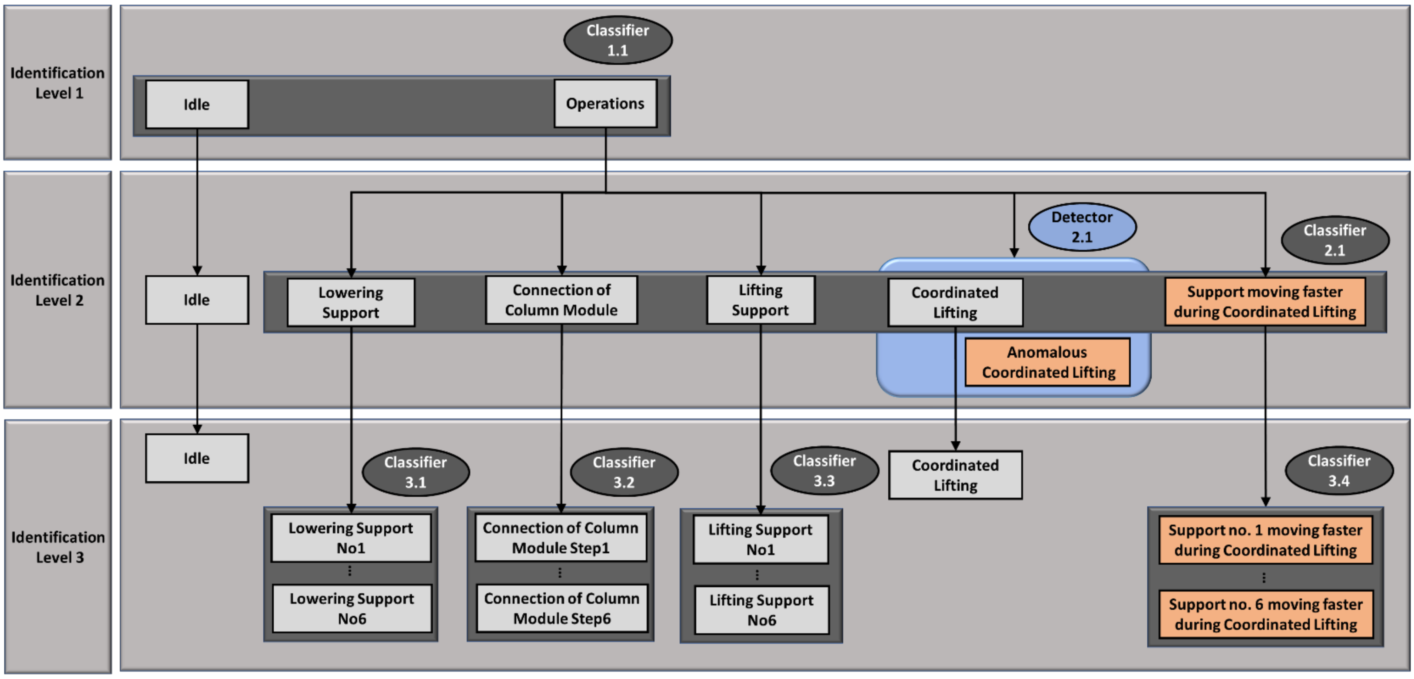


Figure 8.2 Hierarchy of Automated Construction System operations and corresponding detectors/ classifiers

Each identification task is assigned with a classifier or detector followed by hierarchical activity decomposition. A classifier is a machine learning model trained to classify input datasets into various classes. This study refers to the supervised learning models as 'classifiers' (represented by a dark grey box in Figure 8.2) and unsupervised learning models as 'detectors' (represented by a blue box in Figure 8.2). A machine learning model is named 'Classifier IL.N' / 'Detector IL.N,' where IL represents the identification level, and N denotes the number of that machine learning model. For example, Detector 2.1 is the first unsupervised learning model at identification level 2. Figure 8.2 shows the hierarchy of ACS operations and corresponding detectors/ classifiers. The normal operation categories are presented in a light grey box and faulty operation categories in an orange box. Totally 738 instances were used for training, and 315 instances were used for testing across the identification levels. The current study presents only faulty operations associated with Coordinated lifting for introducing the concept of HUS-ML for fault detection. However, the concept can be extended to all other construction operations. After assigning machine learning models at every identification level, HUS-ML training begins.

8.2.1.2 HUS-ML training: Supervised learning

The pre-design study conducted for supervised learning tested six different machine learning algorithms for their performance in the current identification problem. Since the operation classes of the ACS create unbalanced datasets, accuracy will not serve as a good performance measure. The cost associated with misclassifications is better captured by precision and recall. However, a single performance measure is essential for comparing the performance of various prediction models. Hence, the F1 score is selected as the performance measure for selecting the best learning algorithm. F1 score, precision, and recall are computed by equation (8.1) to (8.3).

$$F1\ score = \frac{2\ x\ Precision\ x\ Recall}{Precision + Recall} \quad (8.1)$$

$$Precision = \frac{True\ Positive}{True\ Positive + False\ Positive} \quad (8.2)$$

$$Recall = \frac{True\ Positive}{True\ Positive + False\ Negative} \quad (8.3)$$

The results of the pre-design study at identification level 2 are summarised in Table 8.1. Despite the complexity of the problem and identification level, ANN classifiers delivered the best and consistent performance. Hence ANN is selected for all the supervised learning problems in this study. Once the learning algorithm is selected, the machine learning models can be trained at every identification level. In the current study, normal operations of the ACS and anomalous Coordinated lifting due to asynchronous support movement were recognised during supervised learning.

Table 8.1 Performance of the learning algorithms in recognising major operation classes

Learning algorithm	F1 Score (%)
k-Nearest Neighbour	94.50
Decision Tree	94.79
Support Vector Machines	97.78
Discriminant Analysis	97.31
Naïve Bayes	93.11
Artificial Neural Network (ANN)	100.00

8.2.1.3 HUS-ML training: Unsupervised learning

The present study implements a probabilistic anomaly detection algorithm for identifying unknown faulty operations in automated construction. Anomalous Coordinated lifting caused by noncontact of supports is selected as the unknown faulty operation. The data of this faulty operation class was not used in the training phase.

The best fault detection features were determined through the pre-design study. The ten unique features from eight different sensor locations constitute the 80 features in the study. Gaussian models were generated to detect faulty operations in the input dataset. The pre-design study started with a pair of features for generating the Gaussian model. All unique combinations of features in the 80-dimensional feature space were evaluated to determine the best Gaussian model. Multidimensional Gaussian models with more than two dimensions did not yield good results.

Table 8.2 The best pair of features for Detector 2.1

Feature pair	F1 Score (%)
IQR-AM4 1st Prominent frequency-AM3	99.53

Table 8.2 shows the best pair of features selected for Detector 2.1, which separates the faulty Coordinated lifting operations from the actual Coordinated lifting. AM4 is placed at the middle span of the longest beam, and AM3 is placed at the corner of the structural frame. Hence, any misalignment in the Coordinated lifting can be picked up by these features. The selected features were used for creating the probabilistic model for fault detection. The contours of the Gaussian distribution fitted to the training dataset are shown in Figure 8.3. The estimated threshold, T, for the current problem is 0.106.

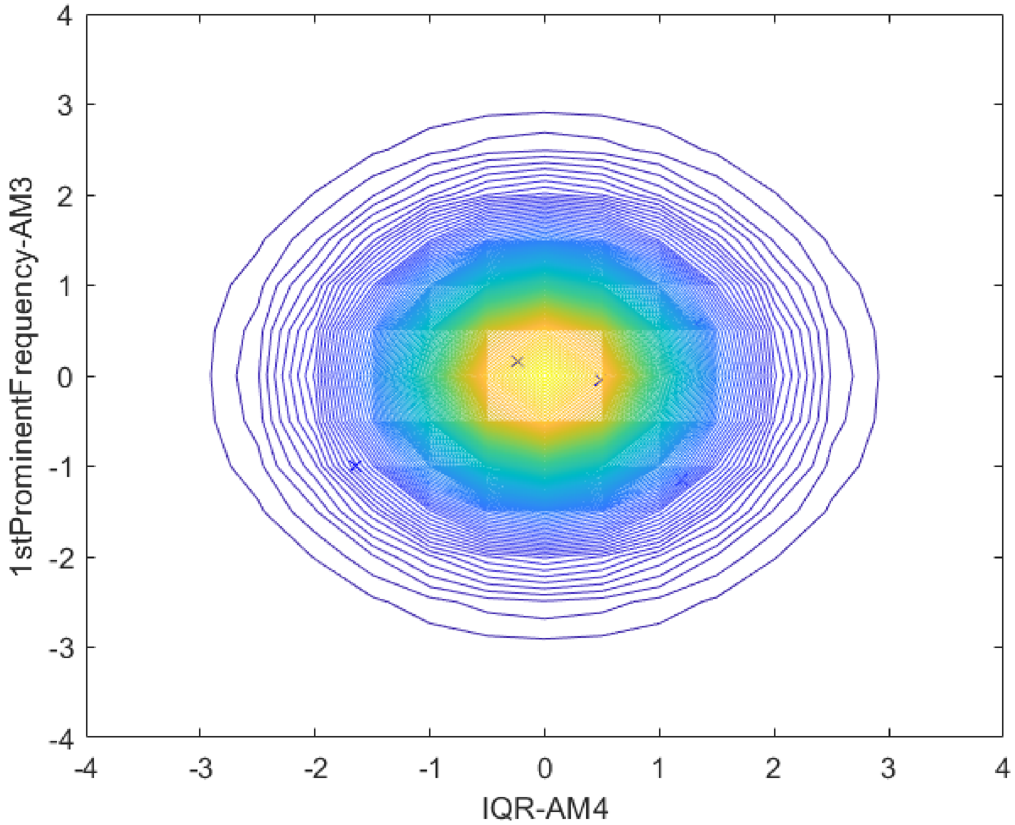


Figure 8.3 Gaussian distribution fit to the training dataset

8.2.2 HUS-ML testing phase

The testing phase in the present study was conducted with the automated top-down construction system in controlled laboratory conditions. The experiments and data collection were performed at once. Thirty per cent of the collected data was reserved for testing the framework; the rest was used for training. An overview of HUS-ML testing is presented in Section 4.3.2.

The known normal operations in this phase comprise operations such as Lowering support, Lifting support, Connection of column module, Coordinated lifting, and sub-operations classes. The faulty operations tested were associated with Coordinated lifting. The faults caused by asynchronous support movement and noncontact support were tested under known faulty operations and unknown faulty operations. The data of unknown faulty operations was introduced to the HUS-ML framework for the first time during the testing.

The acceleration measurements correspond to each operation are supplied as input to the HUS-ML framework. The framework predicts whether the ongoing operation is normal or faulty. If the operation is normal, we proceed to further identification levels and subsequently to the next operations. Otherwise, the HUS-ML warns the operator for corrective actions based on the type of faulty operation class.

8.3 RESULTS AND DISCUSSION

The evaluation results of the HUS-ML framework in identifying the activities and faulty conditions of the ACS and related discussion are presented in this section. The overall performance of the HUS-ML framework compared to that of a Conventional Machine Learning (CML) classification approach is presented in section 8.3.1. The efficacy of the proposed framework in fault detection is elaboratively assessed in section 8.3.2. Section 8.3.3 covers a detailed assessment of the misclassifications based on confusion matrices.

The performance of the HUS-ML framework is evaluated on an unseen dataset in the testing phase. The unseen data involves three categories: 1) known normal operations, 2) known faulty operations, and 3) unknown faulty operations. Here, known operations (normal and faulty) are those operations the framework was trained to identify; and unknown operations (faulty) are the operations framework never trained to identify. The Conventional Machine Learning (CML) classification approach is presented to benchmark the performance of the proposed framework. The conventional approach comprises three identification levels equivalent to that of the HUS-ML framework. Each identification level has a single ANN classifier trained to identify all the operation classes as in a conventional classification problem.

Table 8.3 Overall performance of Conventional Machine Learning (CML) and Hybrid Unsupervised and Supervised Machine Learning (HUS-ML) on the automated construction dataset

Performance measure	Identification framework	Identification level		
		1	2	3
Recall (%)	CML	98.53	77.45	79.98
	HUS-ML	98.53	87.34	86.18
Precision (%)	CML	75.00	71.00	78.18
	HUS-ML	75.00	87.84	87.89
F1 score (%)	CML	85.17	74.08	79.07
	HUS-ML	85.17	87.59	87.03
Accuracy (%)	CML	97.14	82.86	74.29
	HUS-ML	97.14	91.43	85.71

8.3.1 Overall prediction performance

The overall performance of the conventional approach and HUS-ML in activity recognition and fault detection is summarised in Table 8.3. The results are plotted into bar charts as shown in Figure 8.4 to better visualise the performance variation across the identification levels. Both methods attempt to recognise whether the ACS is idle or operating at the first identification level, using a single ANN classifier; hence the performance is the same. However, HUS-ML outperforms the conventional approach at all other identification levels with a significantly high percentage. HUS-ML framework has 6.2 to 9.89 per cent higher recall, 9.72 to 16.84 per cent higher precision, 7.96 to 13.5 per cent higher F1 score, and 8.57 to 11.43 per cent higher accuracy than the conventional approach. As the complexity of the identification problem increases from level one to level three, the accuracy of the conventional approach drops drastically compared to HUS-ML. The variation of the F1 score with identification level is marginal for HUS-ML, while the conventional approach shows inconsistent performance.

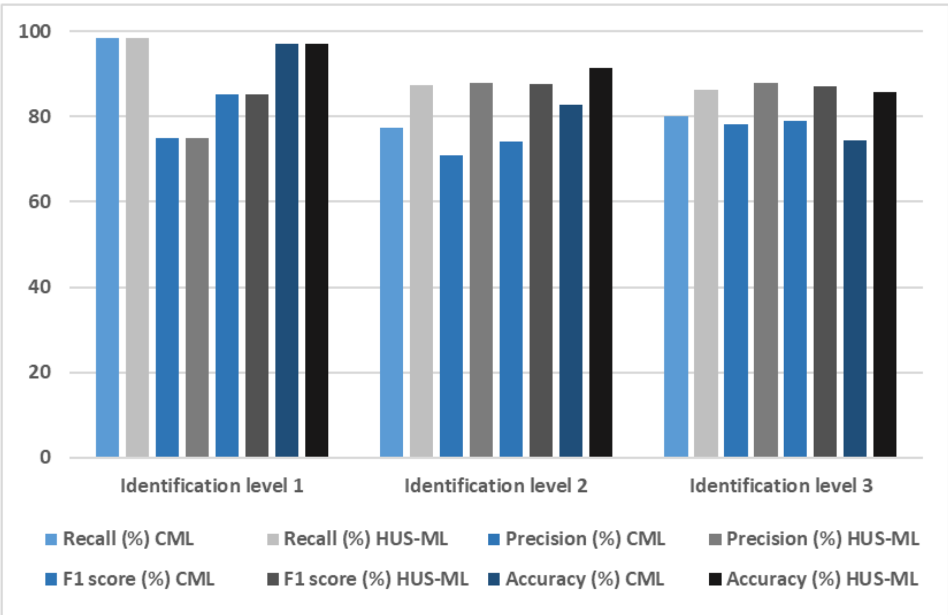


Figure 8.4 Comparison of the overall performance of the conventional approach (CML) and HUS-ML on the automated construction dataset

8.3.2 Performance for fault detection

The HUS-ML framework is proposed to identify known faulty operations and unknown faulty operations for early detection of failure conditions. The current study focuses on the faulty conditions associated with Coordinated lifting operation. Data correspond to two different faulty operations were generated in controlled laboratory conditions. The Coordinated lifting when one of the supports moving faster may result in the overturning of the entire structure. This faulty case is used for supervised learning and is referred to as the known faulty operation class. Noncontact of one of the supports during the Coordinated lifting may cause uneven load distribution and subsequent structural failure. This faulty operation was not used for training the HUS-ML framework but introduced in the testing phase. Thus, it is referred to as the unknown faulty operation class.

Table 8.4 Fault detection performance of HUS-ML and the conventional approach (CML) on the automated construction dataset

Performance measure	Identification framework	Faulty operation class	
		Known	Unknown
Recall (%)	CML	100.00	0.00
	HUS-ML	100.00	66.67
Precision (%)	CML	92.86	0.00
	HUS-ML	96.30	88.89
F1 score (%)	CML	96.30	-
	HUS-ML	98.11	76.19

The fault detection performance of conventional machine learning and HUS-ML at identification level 2 is summarised in Table 8.4. The potential failure cases were first identified at level 2. Therefore, this discussion focuses on fault detection at this identification level. Most of the strategic decisions will depend on the efficacy with which the faulty operations are detected for the first time. Both HUS-ML and conventional approaches show high performance in detecting known faulty operations, and HUS-ML is marginally better. However, conventional machine learning could not identify any of the unknown faulty operations. In contrast, HUS-ML identifies unknown faulty operations with an F1 score of 76.19 per cent. Even though the performance is significantly lower compared to known faulty operations, this is a good start. The current framework needs to be improved further to identify unknown faulty operations. A low recall rate is one of the significant challenges faced by the existing unsupervised anomaly detection algorithms (Pang et al., 2021). Exploring deep anomaly detection algorithms for this purpose is a work in progress.

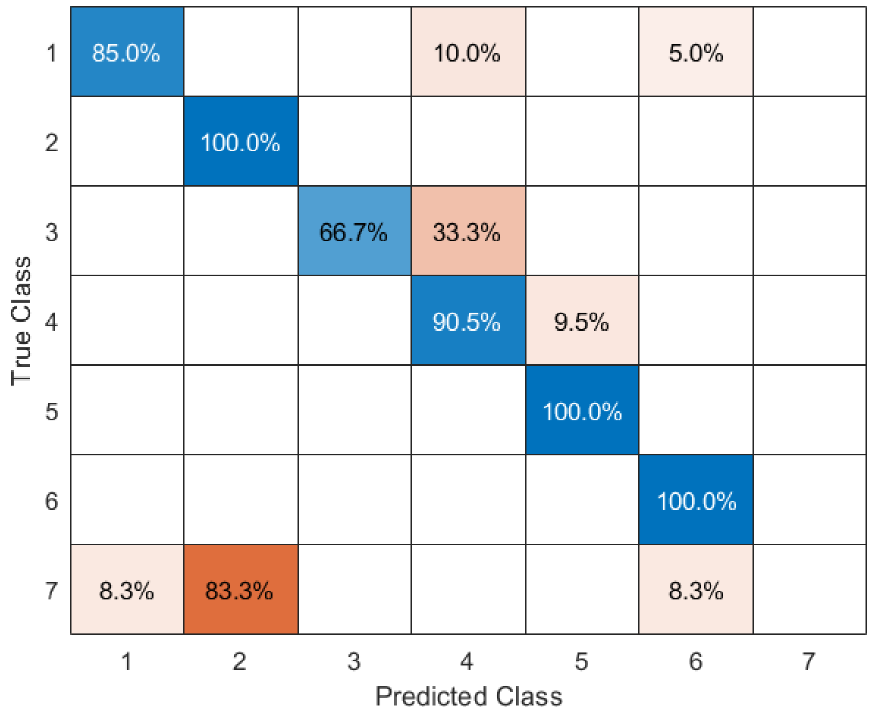


Figure 8.5 Confusion matrix for the conventional approach (CML) at identification level 2 (Results are row-wise normalised); The class labels are 1: Connection of column module, 2: Coordinated lifting, 3: Idle, 4: Lifting support, 5: Lowering support, 6: Known faulty operation and 7: Unknown faulty operation

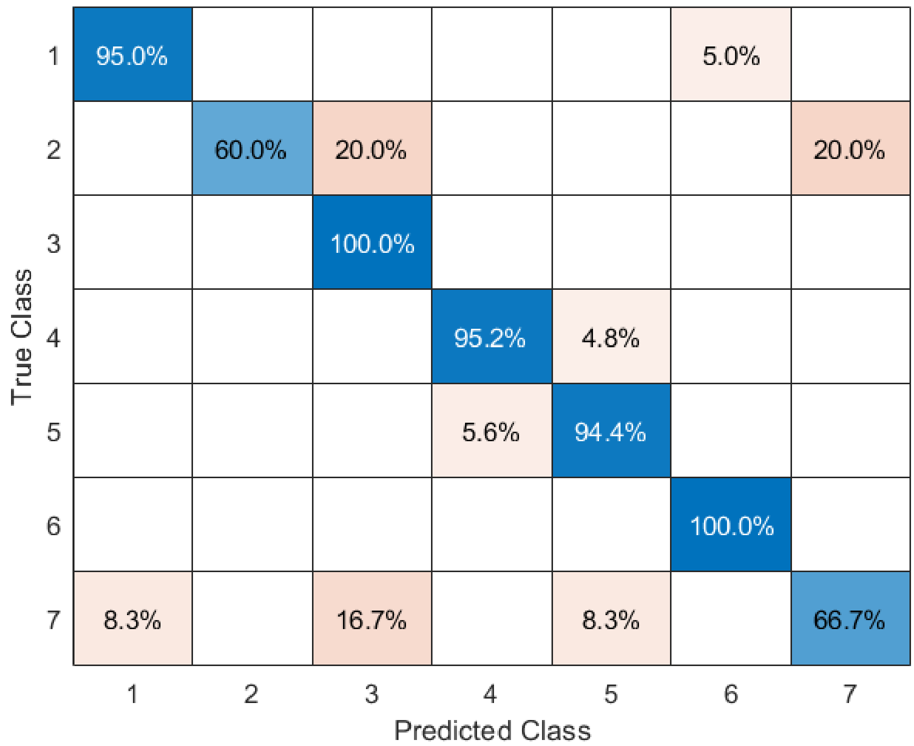


Figure 8.6 Confusion matrix for HUS-ML at identification level 2 (Results are row-wise normalised); The class labels are 1: Connection of column module, 2: Coordinated lifting, 3: Idle, 4: Lifting support, 5: Lowering support, 6: Known faulty operation and 7: Unknown faulty operation

8.3.3 Detailed assessment of misclassifications

Performance of the identification methods based on various statistical measures was discussed in previous sections. A detailed insight on misclassifications can be obtained from confusion matrices. Figure 8.5 and Figure 8.6 show the confusion matrix for conventional classification and HUS-ML at identification level 2. The rows represent true classes, and the columns represent predicted classes. The correct predictions are placed in the main diagonal of the matrix, and off-diagonal elements denote incorrect predictions. The results are row-wise normalised to see how correct and incorrect predictions are distributed within a particular class.

The overall performance measures of the conventional approach are significantly lower than HUS-ML. However, a closer look into the confusion matrix shows that the primary reason for this poor performance is attributed to two categories: Idle and Unknown faulty operation. All other operations are identified with high precision and recall. However, the conventional approach completely fails to identify unknown faulty operations. This exposes the major flaw in the current data-driven fault detection methods. A robust fault detection system should identify known and unknown faulty operations with reasonably good performance. HUS-ML framework has an F1 score of 76.19 per cent in detecting unknown faulty operations. The false negatives in anomalous instances can be reduced with a better Gaussian distribution model. More data corresponds to normal operations can be collected for this purpose. Other sophisticated anomaly detection algorithms and features can also be explored for improving fault detection.

Automated construction monitoring needs to deliver reliable information for critical decision making. Ambiguous or contradicting information can be more dangerous than lack of information. The HUS-ML framework provides detailed information about an activity or faulty condition through three identification levels. The identification models in the HUS-ML framework are arranged hierarchically across various levels. The prediction in the top level is used to refine the prediction at the lower levels. Hence, the information delivered by the HUS-ML framework will be consistent irrespective of the correctness of the identification. Table 8.5 shows inconsistency in the prediction results of both identification methods. Each identification level in the conventional machine learning approach is independent of the other. This ensures high individual performance per level. However, the combined predictions delivered by the conventional approach can be contradicting. If an operation is identified as faulty at level 2 and normal at level 3, this creates more confusion for a human supervisor.

Hence, the reliability of information is equally important as the accuracy. HUS-ML framework strikes a fine balance between reliable and accurate predictions.

Table 8.5 Inconsistent predictions in the conventional approach (CML) and HUS-ML identification

Inconsistency between identification levels	Number of predictions	
	CML	HUS-ML
1 and 2	2	0
2 and 3	13	0
1 and 3	2	0
1, 2 and 3	1	0
Total number of inconsistent predictions	18	0

8.3.4 Significance of the HUS-ML framework in equipment monitoring

Automated construction is faster than conventional construction, with minimal human involvement. Even minute undetected faults in the construction system may result in catastrophic structural failure or severe construction accidents. If the human operator of the system is not warned well in advance, timely mitigation cannot be ensured.

The HUS-ML framework can be applied for monitoring equipment under most situations of failures. The warning is given to the operator based on the severity of impending faults. The situations where warning can be generated using this monitoring framework include the following:

1. Only warning is required but the equipment will work and the operator has to be cautious to take immediate action when required, for example coordinated lifting with a non-contact support
2. The equipment should not be used, immediate action required, for example asynchronous coordinated lifting

3. The equipment is not working and need further investigation, for example unknown faulty conditions

Well defined SOP (Safe/Standard Operating Procedures) and NCR (Non-Conformance Report) are available for existing machinery in the industry. However, these procedures assume that the equipment does not develop faults in the middle of an operation, all possible defects can be enumerated in advance, and all the defects are detectable using simple procedures. Moreover, NCR is prepared manually after a fault is occurred. It does not predict an upcoming failure or detect any new category of failure. However, the HUS-ML framework proactively detect faults and capable of identifying a wide range of known and unknown categories of faults. The Automated Construction System used in this research was newly developed. The prototype is evolving, and further developments are needed before supplying it to the industry as a finished product. The SOP and NCR will be ready for the current ACS during that stage, and the results of this study contribute towards preparing them. The HUS-ML framework proposed in the study lays the foundation for developing a robust monitoring system for the ACS. The framework consists of conceptual components such as algorithms and methodologies for monitoring.

8.3.5 The HUS-ML framework for integrated monitoring system

The framework proposed in this study includes measurement system design, operation identification methodology and fault detection methodology. Therefore, this framework encompasses methodologies from data collection to analysis and detection. The sensing data from various sources are interpreted to derive useful information about the overall operation status that supports decision making. Hence, the HUS-ML framework supports the development of an integrated monitoring system for low-rise automated construction.

The scale of implementation of the HUS-ML framework for a high-rise ACS will be several times higher than that of a low-rise ACS. The monitoring system for each subsystem in a high-rise ACS needs to be independently designed and eventually coordinated using the HUS-ML framework. Information from these subsystems helps to infer the overall operation status.

Consider the ground factory and building push up construction system adopted by AMURAD for high-rise construction and J-up for low-rise construction. The AMURAD comprises nine subsystems and seven end-effectors (Sekiguchi et al., 1997), whereas the J-up system comprises two subsystems (Bock and Linner, 2016b). The complexity of subsystems is much higher in a high-rise ACS compared to a low-rise ACS. Consequently, identification of low-level operations and associated faulty conditions are complex for a high-rise ACS. In contrast, the complexity of monitoring is still manageable in a simpler construction system as in a low-rise ACS.

8.3.6 Generalizability of the HUS-ML framework

The algorithms and methodologies involved in the framework are independent of the type of data, construction equipment or operations involved. The sensor placement methodology is mainly applicable for any type of sensing information in the form of signals. It cannot be directly applied to visual data. In the case of activity identification and fault detection, only the hierarchy of the operations changes from equipment to equipment. Therefore, the HUS-ML framework is generalisable and not restricted to a per-project set of activities unique to that project's geometry. Moreover, the generalizability of the monitoring framework is demonstrated using a completely different application in section 8.4.

8.4 VALIDATION OF THE HUS-ML FRAMEWORK USING A BENCHMARK DATASET

The proposed HUS-ML framework is validated using a publicly available predictive maintenance dataset (Matzka, 2020a) to test its generalizability. Since authentic datasets on faulty conditions are seldom available, Matzka created a synthetic dataset based on actual predictive maintenance conditions in the industry (Matzka, 2020b). The dataset comprises 10,000 data points with six features. The current study has selected a subset of this dataset, excluding the datapoints of random failures and concurrent failures. The proposed framework in this study is trained to identify mutually exclusive faulty conditions. Hence, an accurate estimate of the performance of the framework can be obtained if it is tested on a similar dataset. Therefore, the selected subset of the dataset includes data points that correspond to normal operations, heat dissipation failure, overstrain failure, and power failure. A portion of the heat dissipation failure and overstrain failure was introduced in the training phase. Hence, these failure cases will serve as 'known' faulty operations during the HUS-ML testing phase. The data points correspond to power failure introduced only during the testing phase, representing the 'unknown' faulty operations. More details of these failure cases are described in (Matzka, 2020b).

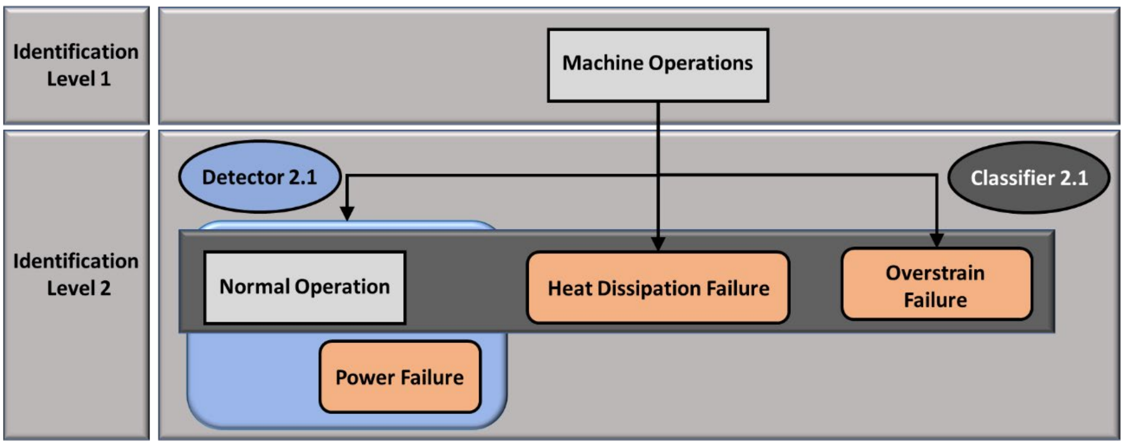


Figure 8.7 Hierarchy of machine operations in the predictive maintenance dataset

Figure 8.7 shows the hierarchy of machine operations in the predictive maintenance dataset and the corresponding classifier/detector. Unlike the ACS operations, the current problem has just two identification levels and fewer classes. The number of training instances for Classifier 2.1 and Detector 2.1 is 6879 and 6798, respectively. The dataset for testing consists of 2980 unseen data points.

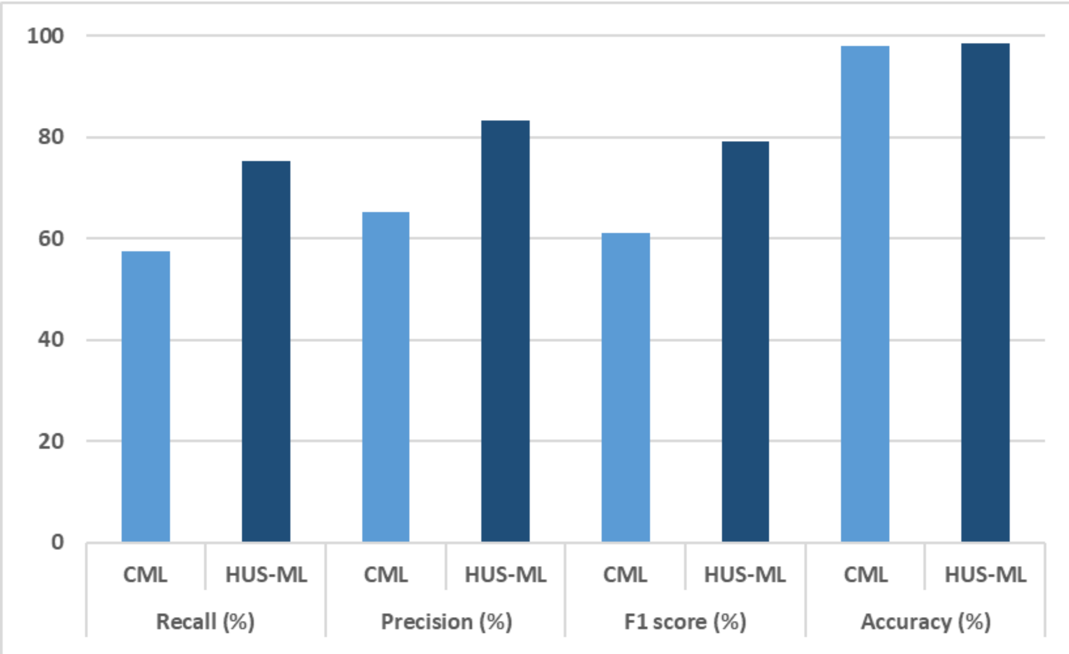


Figure 8.8 Overall performance of the conventional approach (CML) and HUS-ML on the predictive maintenance dataset

The overall performance of the conventional machine learning classification and HUS-ML framework is summarised in Figure 8.8. Both methods show high accuracy, and their performance is comparable (accuracy of 97.99 per cent for the conventional approach and 98.46 per cent for HUS-ML). However, this does not reflect the actual performance of the methods since the predictive maintenance dataset is highly imbalanced. Out of the 9907 instances in the selected dataset, merely 2.7 per cent are faulty operations. This percentage is similar to that of the faulty operations in actual industrial operations. Even if the classifier predicts all the instances as 'normal,' the accuracy of prediction will be high without identifying any failure cases. Therefore, the

F1 score is a better measure to compare the performance of the identification methods. HUS-ML has an 18.07 per cent higher F1 score compared to the conventional approach. The precision and recall values of HUS-ML are also significantly higher than those of the conventional approach. Overall, the HUS-ML framework shows a reasonably good performance (F1 score of 79.14 per cent) on a large and independent dataset.

A close observation of the fault detection results shows that both methods perform equally while identifying known faulty conditions (F1 score of 70.71 per cent). However, the conventional approach completely fails to identify unknown faulty operations. The HUS-ML framework detects the unknown faulty operations with an F1 score of 71.90 per cent. This result is comparable to the result obtained for the same category of faults in automated construction, even on a much larger and diverse dataset. Since the predictive maintenance dataset has only one identification problem, the inconsistency in predictions across levels cannot be evaluated. The automated construction is a complex scenario comprises multiple identification level. However, most industrial applications have at most two identification levels. Hence, HUS-ML may achieve better results compared to the conventional approach in those applications. The results validate the HUS-ML framework on a completely different application domain than construction. Even though the framework needs improvement in fault detection, the current results demonstrate its potential for industrial applications.

8.5 CONCLUSIONS

Activity recognition and fault detection are critical tasks in construction monitoring. The current study proposes a novel machine learning framework called HUS-ML (Hybrid Unsupervised and Supervised Machine Learning) for these tasks. The proposed framework identifies normal operations and known faulty conditions through supervised learning. The unknown faulty conditions are identified through probability models generated by unsupervised learning. This framework is validated through a case study on an ACS. A conventional machine learning approach is applied to the same problem to benchmark the performance of the proposed framework. The proposed framework is also evaluated on a publicly available predictive maintenance dataset to check its generalizability. The unique elements of the framework include newly proposed algorithms for entropy-based sensor placement and hierarchical machine learning classification. Another unique element is the HUS-ML algorithm that combines unsupervised and supervised learning methods for activity recognition and fault detection.

1. The HUS-ML framework shows promising results in identifying low-level details of normal automated construction operations that may potentially assist in locating the sources of faulty conditions. The framework also detects early signs of failure through Gaussian models with limited data. The HUS-ML framework outperforms the conventional approach in activity recognition and fault detection with 6.2 to 9.89 per cent higher recall, 9.72 to 16.84 per cent higher precision, 7.96 to 13.5 per cent higher F1 score, and 8.57 to 11.43 per cent higher accuracy.
2. The HUS-ML framework identifies known faulty operations and unforeseen faulty operations through a two-stage fault detection strategy. The focus of most data-driven methods for fault detection is limited to known fault classes. The conventional approach completely fails to identify unknown faulty operations. In contrast, the HUS-ML framework achieves an F1 score of 76.19 per cent in detecting unknown faulty operations.
3. The HUS-ML framework delivers consistent and accurate predictions across activity levels. The conventional approach, which does not use information from

previous identification levels, produces inconsistent predictions across levels. Therefore, the HUS-ML framework is more suitable for automated construction monitoring than the conventional approach for providing reliable and unambiguous information.

4. The performance of the proposed framework on a predictive maintenance dataset demonstrates its potential for machine fault detection. The framework achieves an overall accuracy of 98.46 per cent and an F1 score of 79.14 per cent on this dataset.

CHAPTER 9

CONCLUSIONS

This chapter summarises the conclusions of this research. First, a summary of key aspects of the work is given in Section 9.1. The significant conclusions of the study are presented in section 9.2. The main contributions to knowledge and practice are described in section 9.3. Finally, the limitations of the work and directions for future research are presented in section 9.4.

9.1 SUMMARY

This research aims to develop a robust monitoring system for automated construction that accurately identifies activities and faults. The specific research objectives addressed in this research are the following.

1. Develop an automated operation recognition and fault detection framework which takes into account specific requirements of the automated construction domain, such as:
    1.1. High accuracy of identification
    1.2. High level of details of activities
    1.3. Ability to detect early signs of failure with limited data
2. Design algorithms and methodologies for the efficient implementation of the framework. This includes algorithms for:
    2.1. Sensor placement
    2.2. Operation identification
    2.3. Fault detection
3. Design the experimental setup and evaluate the feasibility of the application of the framework on a full-scale automated construction system.

The methodology adopted for the current research is quantitative theory building based on case studies. This research methodology involves the development of a conceptual framework followed by empirical verification and iterative modifications.

Objective 1: A framework for automated construction monitoring has been developed. The critical conceptual components of the framework consist of a sensor placement strategy, an operation identification methodology, and a fault detection method. The implementation of this monitoring framework starts with the measurement system design using the preliminary measurements during automated construction. The configuration of the measurement system is determined through the sensor placement methodology. Then the sensor measurements are collected from the Automated Construction System during operation and supplied to the monitoring framework. The hierarchical operation identification methodology extracts a high level of activity details for construction monitoring. Besides, the hierarchical problem formulation ensures high accuracy of identification. The known operations and faulty conditions are recognised during supervised learning, and the unknown faulty conditions are detected through probabilistic models. The datasets of operating states which potentially result in failure are used to represent the anomalous operations. The proposed framework detects the early signs of failure with limited data. The algorithms of the proposed framework are iteratively modified based on their performance during validation.

Objective 2.1: Design of measurement system involves selecting sensors and their positions, data acquisition system and other related aspects. A new sensor placement method has been developed in this research in which derived features are used for evaluating information content at sensor locations. The information content of a parameter is estimated by Shannon's entropy, a concept derived from the information theory. The features used for sensor placement are also used for machine learning classification; therefore, there is consistency in the use of variables in the two methods.

Objective 2.2 and 2.3: New algorithms for operation identification and fault detection have been developed. The hierarchical operation identification methodology divides the identification problem into multiple classification levels with increasing complexity. Machine learning classifiers are assigned to solve the identification problems. The information from the previous level is used to refine the identification at a particular level. This problem formulation ensures high accuracy of identification and extracts a high level of details of activities. The concept of anomaly detection in machine learning is explored for detecting faulty operations. Gaussian models are generated to represent the characteristics of normal operation data. Anomalous operations are identified based on the deviations from the probabilistic model.

Objective 3: The proposed framework has been validated on an actual automated construction system that was custom designed and fabricated as part of this research. This system has been developed for low rise building construction that follows an automated top-down construction method. Acceleration measurements from the structure were used for identifying operations and faulty conditions. The experiments were conducted in a controlled laboratory condition under the supervision of trained experts. It involves normal operation cycles and potential faulty conditions in the automated construction. The experiments which cover normal operations involve two complete cycles of top-down construction. The experiments for faulty conditions were designed to capture the early signs of failure during construction within the safety norms. Each component of the framework was independently validated, the sensor placement methodology, the identification framework, the fault detection method and finally, the HUS-ML framework. The performance of the proposed framework was benchmarked by comparing it with conventional approaches. The algorithms for operation recognition and fault detection were iteratively modified to obtain the desired performance. Advanced deep learning classifiers such as LSTM (Long Short-Term Memory) networks and various data augmentation methods were explored for identifying automated construction activities. The generality of the proposed framework was assessed through its application on a benchmark dataset.

9.2 CONCLUSIONS

The conclusions from this research are divided into two parts. The primary conclusions contain significant contributions to the body of knowledge, and the secondary conclusions are related to the particular case study that has been adopted for validation.

9.2.1 Primary conclusions

1. The performance of activity recognition can be enhanced by refining the identification problem through the incorporation of hierarchical relationships among activities.
2. Early signs of failure in construction equipment can be effectively detected through unsupervised learning techniques using probabilistic models that represent the normal operation patterns.
3. A two-stage fault detection strategy that combines supervised learning followed by unsupervised learning identifies unforeseen faulty operations better than conventional supervised learning methods.

4. The hierarchical structuring of the identification problem ensures consistent prediction performance irrespective of the complexity of the problem. Besides,

reliable and unambiguous information for decision making can be delivered through this problem formulation.

5. The sensor placement methodology based on derived features evaluates the significance of a sensor location based on the quantity and quality of data from that location. The entropy in this method estimates the amount of useful information from a location. The derived features incorporate their effectiveness in operation identification and fault detection. In addition to that, this sensor placement method shows the potential for feature selection.

9.2.2 Secondary conclusions

1. The sensor placement method proposed in this study is efficacious for problems involving a large number of potential sensors and high dimensional feature space. It can be adopted for structural health monitoring and construction monitoring applications.
2. A particular sensor is selected during sensor placement only when it offers any new information. Therefore, the addition of variables beyond a certain threshold does not improve the identification of instances.
3. The order of selection of new sensors is based on their mutually exclusive information content from the previously selected sensors. Hence, each iteration of the sensor placement methodology selects different types of measurement locations.
4. The method of calculating the information content influences the features selected by the sensor placement methodology. The interquartile range is the most frequently selected feature because the entropy is calculated based on the distribution of the variables.

5. Artificial neural network (ANN) is identified as the best machine learning algorithm for recognising automated construction operations irrespective of the problem formulation or classification level. The high noise tolerance of these classifiers shows their potential for application in actual construction sites with reasonable accuracy.
6. Complex learning algorithms need not necessarily result in better performance. Lack of variety in the original dataset during data augmentation greatly affects the performance of the deep learning classifiers. Therefore, the traditional machine learning classifiers outperformed the deep learning classifiers in identifying major automated construction operations.
7. Augmenting data may not deliver better results if it alters the characteristics of the original dataset. The selection of appropriate data augmentation methods and the design of network architecture demands great expertise. Even though deep learning may avoid feature selection, domain knowledge is necessary to develop a robust classifier for activity recognition.
8. Activity recognition problems involving operations with signature vibration or frequency require classifiers trained with frequency-domain features. LSTM classifiers trained with limited time-domain data may be inadequate for vibration-based activity recognition.

9.3 CONTRIBUTIONS OF THE RESEARCH

9.3.1 Contributions to knowledge

This research contributes to the body of knowledge and construction practices. The knowledge contributions are:

1. The HUS-ML framework for automated construction monitoring that has the following attributes:

a) Identification of automated construction operations with consistent performance

b) Extraction of details of low-level construction activities

c) Detection of early signs of failure in construction operations

d) Identification of unknown faulty conditions associated with construction equipment

e) Detection of faulty conditions even with limited data

f) Applicable for equipment in construction and other domains

2. A new operation identification methodology that improves the accuracy of existing methods by incorporating domain knowledge in the mathematical formulation of the problem
3. A sensor placement methodology based on derived features that ensures consistency in the estimation of information content for sensor placement and construction monitoring

9.3.2 Contributions to practice

In addition to the theoretical contributions, the results of this study also have some implications for the construction practices. The framework proposed in this study includes measurement system design, operation identification methodology and fault detection methodology. Therefore, this framework encompasses methodologies for various components of an automated monitoring system from data collection to analysis and detection. The sensing data from various sources are interpreted to derive useful information about the overall operation status that supports decision making. Hence, the HUS-ML framework supports the development of an integrated monitoring system for low-rise automated construction.

The application of such a monitoring system enhances the current construction practices. The real-time information about all the construction activities helps to ensure the correct execution of the operations. Besides, it also helps to ensure structural integrity and good quality construction. The level of details of operations identified potentially assist in locating the sources of faulty conditions in an ACS. The low-level operation details extracted may also be utilised to estimate the cycle time and other productivity measures accurately.

Detecting early signs of failure ensures corrective actions and accident mitigation in time. The data collected for safety monitoring can also be used for monitoring construction progress and estimating productivity. The construction progress information can be made accessible to various stakeholders for assessing the performance of the whole project. The developed framework can help take appropriate control actions and act as a support system for taking project management decisions.

9.4 LIMITATIONS AND FUTURE WORK

The proposed framework is developed for detecting mutually exclusive faulty operations. Detection of faults due to multiple causes need further investigation. The fault detection performance of the current model can be enhanced by deep anomaly detection algorithms and more complex features. Collecting more data of normal operations can improve the Gaussian prediction model. Improving the prediction performance for unknown faulty classes need to be explored further.

The current research was conducted using a laboratory prototype of an Automated Construction System. The experiments were conducted in a controlled environment. The actual automated construction may have a much more complex system, and the disturbances from surroundings might be stronger. Collecting sensor data from the structure is still possible in that scenario with wireless sensors. However, the sensitivity requirements of the sensors should be evaluated carefully.

Automated construction experiments are time-consuming and expensive. Collecting a large quantity of data is often not feasible. Simulated models of the automated construction system can generate synthetic data for addressing the problem of small datasets. Data augmentation methods that do not alter the characteristics of original datasets are another option.

The current prototype has the capacity required for actual construction site applications. However, various safety, legal and ethical aspects must be considered before certification, patenting and commercial development of this system. The current version of the prototype involves machine to human interaction during the connection of the structural modules. The safety measures for labours and potential failure conditions must be identified to demarcate the standard operating procedure.

APPENDIX A

CATEGORIES OF AUTOMATED TOP-DOWN CONSTRUCTION

A.1 AUTOMATED TOP-DOWN CONSTRUCTION

The conventional construction method progresses from bottom to top, starting from the foundation level. The major cost in automated construction is associated with lifting. The bottom to top method of automated construction involves lifting the entire central operation unit after completing each floor. For the construction of the low-rise building where reducing the cost is one of the prime criteria, automated top-down construction is the best solution. All activities in automated top-down construction are carried out at the ground level. This will permit a high level of automation since all the equipment can be installed at the ground level.

The direction of construction progress for the automated top-down construction method is from top to bottom (Raphael *et al.*, 2016; Harichandran *et al.*, 2019b, 2019a, 2020b, 2021). The construction starts from the topmost floor of the building. The lower floors are added one by one below the completed floors and lifted in sequence. The load-bearing parts of the structure are modularised into multiple components and assembled during various stages of construction. The 'ground factory and building push-up' method is a similar automated construction method. However, heavy machinery was deployed to handle larger and heavier building components (Sekiguchi *et al.*, 1997; Bock and Linner, 2016b). The modularisation of structural components enables light equipment in the automated top-down construction method. This saves the time and cost of installation and transportation of equipment at the beginning of construction.

The compact equipment used in this method can be easily installed and dismantled at the ground level itself. It can also be transported using a small vehicle. Since the machinery is arranged inside the core of the structure to be constructed, it occupies limited space in the construction site. This is a beneficial attribute for construction in space-constrained areas such as cities.

A.2 CATEGORIES OF CONSTRUCTION

Specific operations and their sequence in the automated top-down construction vary with structural configuration and the Automated Construction System (ACS). Therefore, automated top-down construction can be categorized into two. The first category uses a specific structural configuration that maintains stability even while removing one support. This category follows operation sequences that allow the connection of one column module at a time. One cycle of operations in the automated top-down construction category I can be summarised as follows:

a. Assembly of the topmost beam and column modules of the structure around the ACS and supporting the structure at each column positions

b. Coordinated lifting of the assembled structure by lifting all supporting platforms simultaneously to one column module height

c. Lowering the supporting platform to add a column module

d. Connecting the column module to the previously installed column module

e. Lifting the supporting platform until the load of the structure is transferred completely

f. Repeating steps 'c' to 'e' for other supporting platforms in the same level of construction

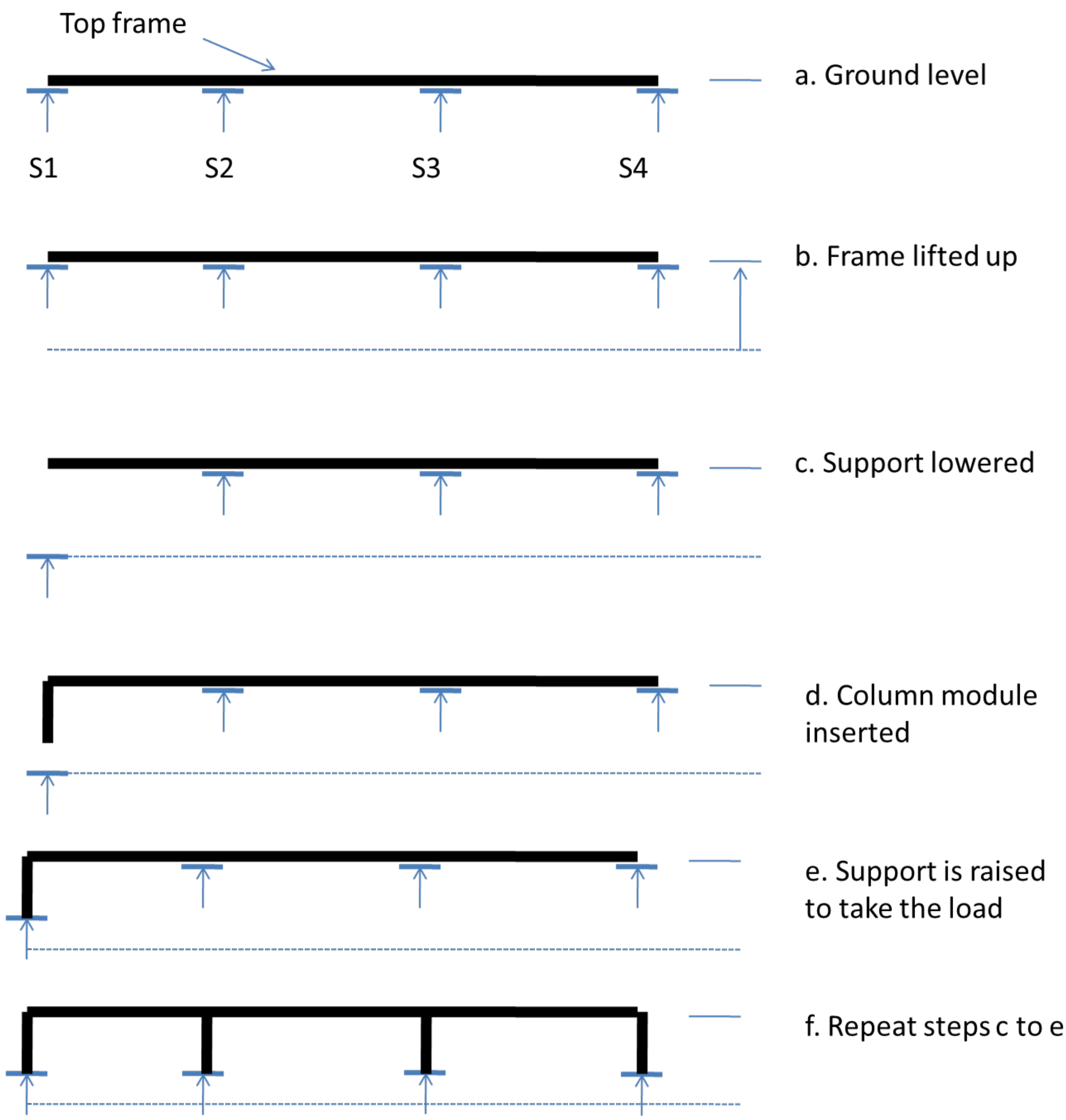


Figure 9.1 One cycle of operations in the automated top-down construction category I

Figure 9.1 is a simplified schematic representation of the above steps where S1, S2, …, S4 represent support 1, support 2, …, support 4. Each cycle of operations completes one level of the structural frame. Several operation cycles are required to complete a floor of the structural frame. The number of cycles depends on the height of one column module and the clear height between two floors of the structural frame.

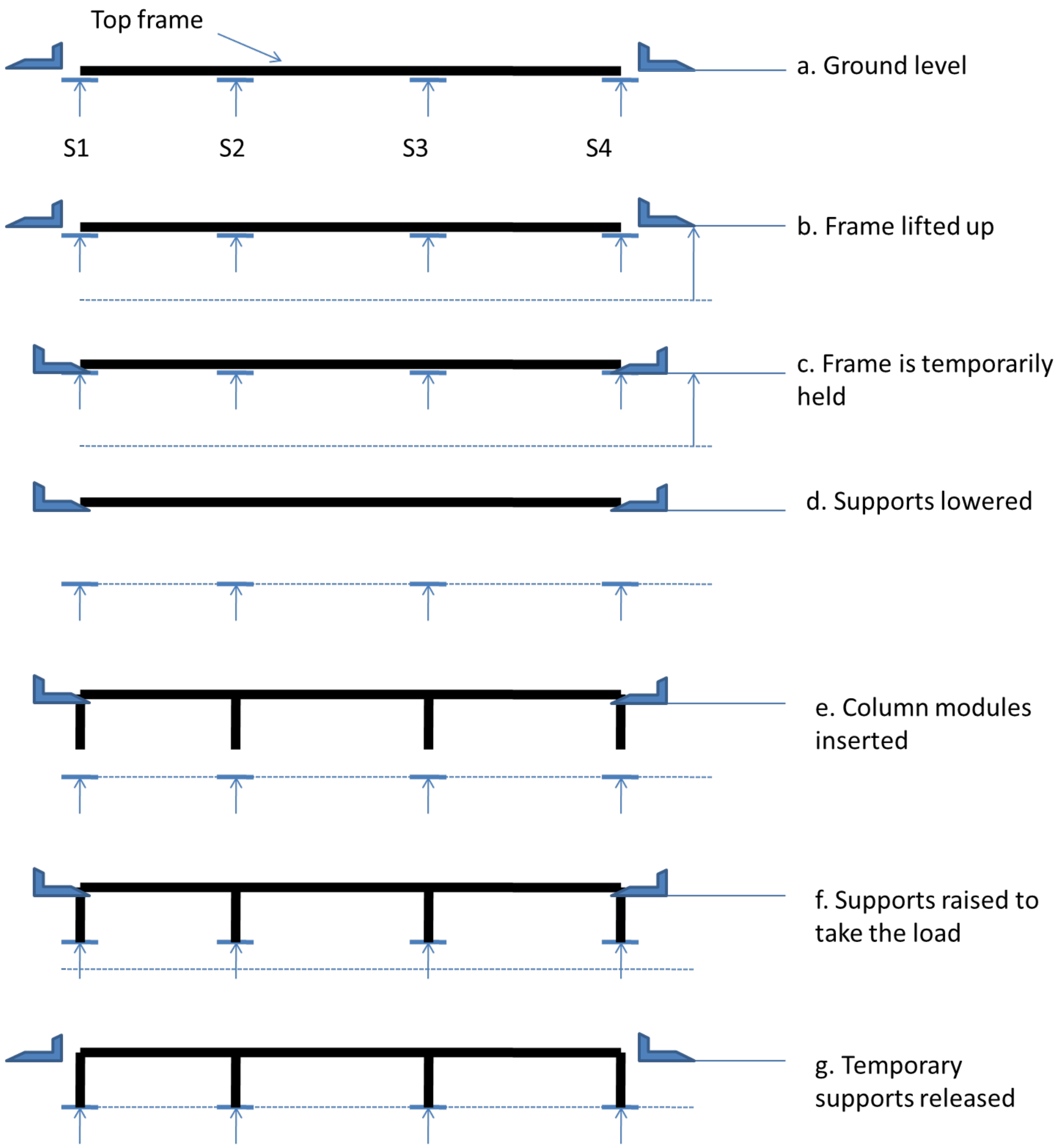


Figure 9.2 One cycle of operations in automated top-down construction category II

The second category of automated top-down construction uses construction systems that have an additional feature to hold the structure temporarily while the modules of the lower floor are being connected. In this category, the operations will be similar to the previous one except in the case of connections. Instead of connecting one column module at a time, all the column modules in a particular construction level can be connected simultaneously. The construction time reduces considerably compared to the first category. However, the second category demands slightly more intricate equipment which can hold the entire structure at a time. Figure 9.2 shows a simplified schematic representation of the automated top-down construction category II where S1, S2, …, S4 represent support 1, support 2, …, support 4. This figure is for illustration of the construction concept only.

Automated top-down construction is a highly productive and sustainable method. This involves the construction of the core structural members, segment by segment in a systematic way. The machines required for the construction are placed on the ground, and the structural frame of the building will be pushed up without having the assembly system climbing up with the structure. The advantage of this type of construction is that all the activities are performed at the ground level, and heavy equipment such as tower cranes are not needed.

APPENDIX B

DEVELOPMENT OF AUTOMATED CONSTRUCTION SYSTEMS

B.1 INCREMENTAL DEVELOPMENT METHOD

The low-rise Automated Construction System (ACS) prototypes and structural systems are developed as a part of the experimental setup for this research. The purpose of the experimental setup is to validate the methodology that has been developed in this work. The ACS in this project has been developed incrementally. Small prototypes have been developed and tested in the laboratory. The system is evaluated from the functional point of view as well as the cost and efficiency of operations.

Several versions of prototypes were tested with different types of structural elements, mechanical elements and levels of automation. The initial prototype used rectangular timber modules connected manually (wooden structure v1) (Raphael *et al.*, 2016). Only coordinated lifting was automated in this prototype (ACS prototype one). This prototype established the feasibility of the construction scheme. Later, another prototype was implemented to test the automated connection of steel modules using bolts. This prototype used a camera and AI-based image recognition to locate the bolt holes. A custom gripping-alignment system was also implemented to insert the bolts and make the connections. However, the scheme was only partially successful because of the low precision of the fabrication work. The holes on the connecting plates and steel sections had to be perfectly aligned to insert the bolts correctly. Even minor imperfections in the alignment would cause high friction between the surface of the bolt and the edge of the hole. High precision fabrication considerably increased the cost of construction. Hence, this system was not pursued further.

A highly automated construction system (ACS prototype two) is developed to construct a structural system with rectangular steel modules (steel structure v1). Due to the high cost of the prototype and heavy modules of the structural system, further studies were focused on reducing the cost of the prototype and the weight of the structural modules. Later versions of the structure used steel pipe sections connected manually using couplers (steel structure v2) (Harichandran *et al.*, 2019b, 2019a, 2020b, 2020a, 2021). These were found to be economical as well as efficient in operations. The modified construction system (ACS prototype three) is partially automated but has a considerably lower cost than the previous prototype. Hydraulic motors (hydraulic motor system v1) and electric motors (electric motor system v1 and v2) were tested for lifting systems. Various prototypes that have been tested are described in this section.

B.1.1 Design of modular structure

The cost associated with lifting operations amounts to a significant part of the overall cost for automated construction. Since the central operation unit of automated top-down construction is on the ground floor, the only cost of lifting for the structure. The modularisation of structural components reduced the weight and cost of lifting and made the components easier to construct.

The first version of the structural system comprises wooden modules of a rectangular cross-section (wooden structure v1). Each module was 400 mm x 200 mm x 400 mm made of 20 mm thick wooden planks. Wooden interlocking components connected the modules. This first version of the structural system is used in the first ACS prototype, in which connections were made manually by screwing the components (Figure 9.3 and

Figure 9.4). Similar structural components are used for the second prototype of the ACS (Figure 9.5). However, the components with the same dimensions are fabricated in steel (steel structure v1). The modules were modified at the top and bottom edge for interlocking, similar to Lego blocks. Additional holes were made at these edges for inserting interlocking pins to secure connection.

The second version of the structural system comprises mild steel pipe sections with external threading on both ends (steel structure v2). Couplers connect the column modules with internal threading. The connections at the corners of the structure and connection between bream and column modules are made by custom made universal steel joints. This structural system is used in ACS prototype three (Figure 9.6) and is deployed for conducting the automated construction experiments in this study. Currently, the connections of this structural system are made manually. However, there is a high potential for automating this connection by slight modification in the construction system. An additional facility consists of a gripper holding the top module while another gripper holding and rotating the bottom module facilitates automated connection. Further modification of the ACS prototype three for automating the connections is in progress.

The structural configuration influences the category of automated top-down construction and the configuration of the construction system. Automated top-down construction category I demands a structure with additional columns that ensure stability even in removing one support (ACS prototype one and ACS prototype three). However, automated top-down construction category II can be deployed either with a typical structure or with a structure having additional supports (ACS prototype two).

Figure 9.3 An overview of the ACS prototype one

B.1.2 Design of Automated Construction System (ACS)

The ACS is designed based on the structural configuration and the category of automated top-down construction. The construction system has as many supports or lifting platforms as the number of columns in the structure. Automated top-down construction category I require machines capable of lifting and lowering individual support of the structure. Automated top-down construction category II can be implemented only if the construction system can hold the complete structure at any stage of construction. The high weight of lifting, in this case, demands hydraulic systems. That might increase the cost of construction. Electric motors serve economic lifting options. However, the speed and weight of lifting will be reduced. All construction systems in this study are partially automated with varying degrees of automation. The evolution of the automated top-down construction method through various prototypes are described in the next section.

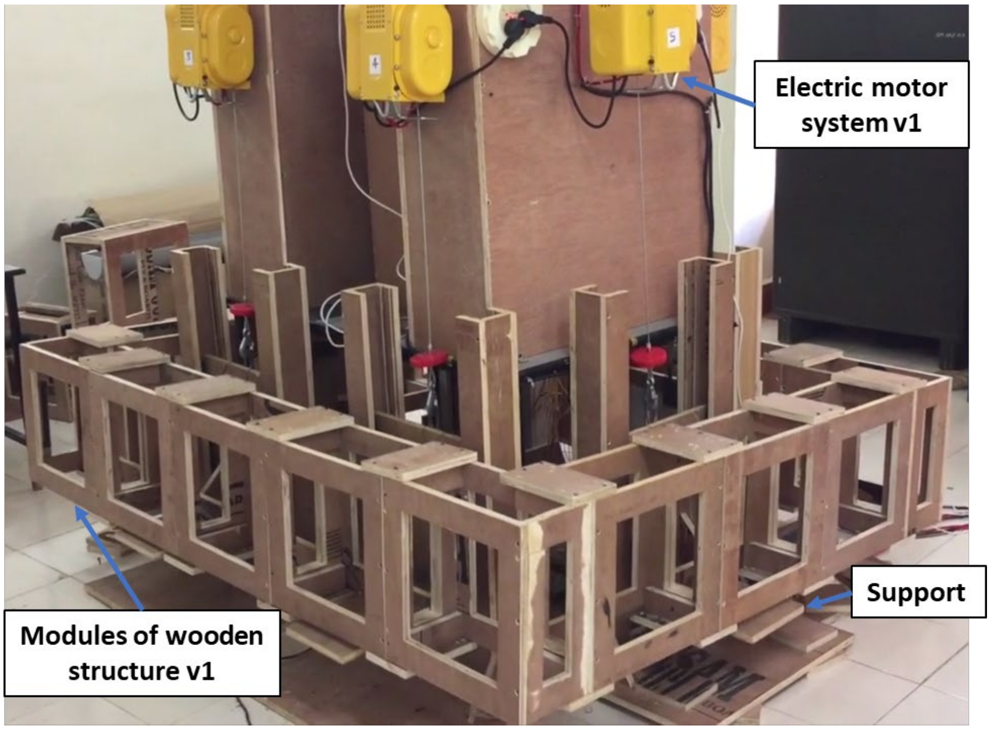


Figure 9.4 Coordinated lifting of beam assembly at the topmost level using ACS prototype one

B.1.3 Development of Automated Construction System (ACS)

ACS Prototype one (with wooden structure v1 and electric motor system v1)

ACS Prototype one was meant to demonstrate the top-down construction method (Raphael *et al.*, 2016). The design focus for this construction system was to arrange the machines within the structural frame and to enable coordinated lifting. This prototype follows automated top-down construction category I. The construction system has six lifting machines which can be operated independently or simultaneously based on requirements (Figure 9.3 and Figure 9.4). The lifting machines are operated by an electric motor hoist with wire ropes (electric motor system v1). The light wooden structural system (wooden structure v1) were connected manually. The data from height sensors and pressure sensors were used to operate and control the construction system by Arduino microcontrollers. The operations in one cycle of automated top-down construction using ACS prototype one are given in Table B.1. The operations are numbered based on their order of sequence in the construction cycle.

Table B.1 Operations in one cycle of automated top-down construction using ACS prototype one or using ACS prototype three

Operation number	Operation description
1	Coordinated lifting
2	Lowering support no. 1
3	Connection of column module step 1
4	Lifting support no. 1
5	Lowering support no. 2
6	Connection of column module step 2
7	Lifting support no. 2
8	Lowering support no. 3
9	Connection of column module step 3
10	Lifting support no. 3
11	Lowering support no. 4
12	Connection of column module step 4
13	Lifting support no. 4
14	Lowering support no. 5
15	Connection of column module step 5
16	Lifting support no. 5
17	Lowering support no. 6
18	Connection of column module step 6
19	Lifting support no. 6

ACS Prototype two (with steel structure v1 and hydraulic motor system v1)

The ACS prototype two has a custom-designed construction system consisting of hydraulic motors (hydraulic motor system v1) for lifting and connecting steel structural frames (Figure 9.5). Each machine in this construction system can support the previously constructed structure while building two columns. The machine has a lifting capacity of two-ton per support.

The system lifts the partially constructed structure using a hydraulic ram controlled by pumps and valves. The pump will be turned off when the signal from the control system prompts the electric motor. This happens when the piston of the hydraulic ram arrives at the required height. The load of the structure will be held by the piston when the valve is closed.

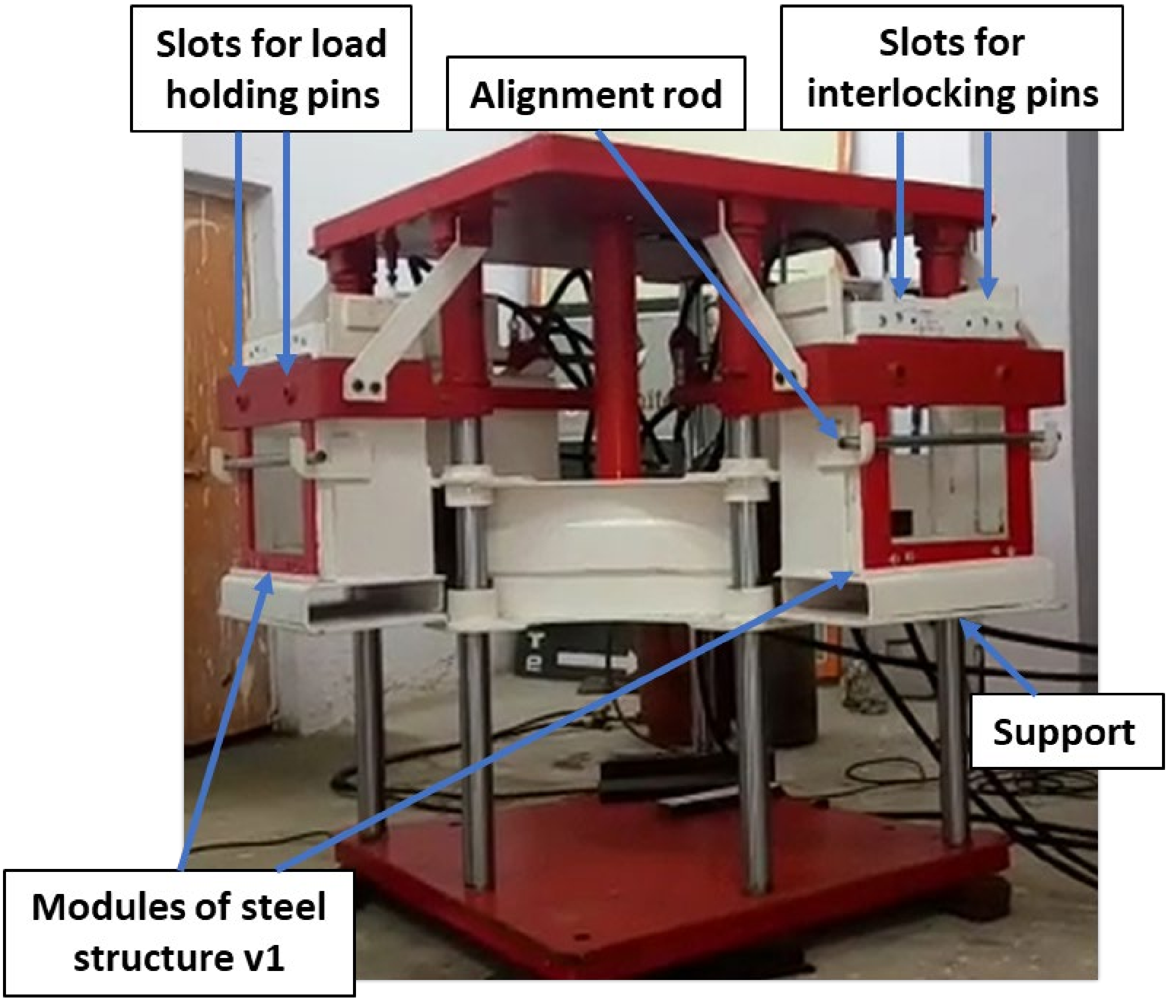


Figure 9.5 Holding of corner column modules using one machine in ACS prototype two

The machine operates with structural modules (beam and column modules) made of rectangular box sections (steel structure v1). The box sections interlock and have holes for connecting modules using interlocking pins. The hydraulic system automatically inserted the interlocking pins at the appropriate time. Besides, there are also load holding pins for temporarily holding the structure before support is lowered. Proximity sensors are installed to ensure the proper insertion of pins in each slot. There are light indicators to show the status of load holding pins (when they finish holding or releasing the modules). The supporting platforms are designed to fit the rectangular modules. They also allow the movements of pistons to insert both load-holding pins and interlocking pins from the rear end. The supports have a provision to insert the alignment rod, which keeps the module in position and avoid the module from falling off in any situation during lifting.

Table B.1 Operations in one cycle of automated top-down construction using ACS prototype two

Operation number	Operation description
1	Coordinated lifting with loaded supporting platforms
2	Holding column modules (8 no.) using load holding pins
3	Coordinated lowering with empty supporting platforms
4	Loading column module 1 to supporting platform 1
5	Loading column module 2 to supporting platform 2
6	Loading column module 3 to supporting platform 3
7	Loading column module 4 to supporting platform 4
8	Loading column module 5 to supporting platform 5
9	Loading column module 6 to supporting platform 6
10	Loading column module 7 to supporting platform 7
11	Loading column module 8 to supporting platform 8
12	Coordinated lifting until column modules interlock
13	Connection of column modules (8 no.) using interlocking pins
14	Releasing column modules (8 no.) from load holding pins

The sequence of operation at a support is as follows: In the first cycle, each module is placed on each supporting platform, aligned at the designated place using an alignment rod. In the next step, the module is lifted by the load lifting cylinder by 50 mm to interlock with the module above. The interlocking pins are pushed into position by the pin locking cylinder, and the load holding pins are retracted. Then the load lifting cylinder lifts the module by one module height. After that, the load holding pins lock into the module and hold it in place. Then the first alignment rod is removed. In the reverse cycle, the load lifting cylinder is lowered by a height equal to one module height plus 50 mm clearance. The pin locking cylinder is retracted, and the new module is placed. This process repeats until the entire frame is constructed. Note that the operations at just one support are described here. The same operations were carried out simultaneously for all other supports. The ACS prototype two follows automated top-down construction category II. The whole operations per cycle for ACS prototype two is given in Table B.1. This ACS prototype is designed for a structural system with two corner columns. Hence, there are eight columns for the structure, and four machines are required to complete the construction of the structural frame (steel structure v1).

Even though the construction system was highly efficient in terms of speed and ease of construction, the cost was high. The rectangular modules were heavy (30.8 kg), and two labours were required to load them into the construction system. This version of the construction system encouraged one to look into lighter structural configuration and economical lifting options.

ACS Prototype three (with steel structure v2 and electric motor system v2)

The ACS Prototype three is an improved version of ACS prototype one and follows the automated top-down construction category I. The construction system consists of six lifting machines with a stepper motor for precise operation (Figure 9.6). Each machine has a lifting capacity of two-ton. Similar to ACS prototype one, the lifting machines can be operated individually or simultaneously. The construction system is controlled by programmable Arduino microcontrollers. The operations and sequence are the same as the ACS prototype one (Table B.1). However, the structural system is made of steel pipe sections. This reduced the overall weight of the components considerably compared to that of the previous ACS prototype. Therefore, the equipment in this construction system is lighter and compact than the previous version. Even though the speed of construction is reduced, the current version is much more economical. This ACS prototype is selected for conducting the automated construction experiments in this study.

Figure 9.6 Construction in progress using ACS prototype three

APPENDIX C

PERFORMANCE COMPARISON OF AUTOMATED CONSTRUCTION SYSTEMS

C.1 PERFORMANCE OF AUTOMATED CONSTRUCTION SYSTEMS

The prototypes of automated top-down constructed systems are evaluated based on construction time, cost, automation level, the skill level required for construction, and ease of transportation, assembling and disassembling of construction systems. Table C.1 shows a brief description of the specifications of each ACS prototype. Table C.2 presents a comparison of average cycle time estimated through experimental studies and other details. The experimental studies on all ACS prototypes involve two unskilled workers for construction and one trained worker operating the machine. Here, cycle time refers to the time for completing one cycle of operations of a particular construction system. That is the time for completing one level of construction. One floor of the structural system contains several construction levels.

Table C.1 Specifications of ACS prototypes

ACS prototype	Category of automated top-down construction	Structural system		Construction system		Number of operations per cycle	Number of lifting machines required
		Material	Version	Operation unit	Version		
1	I	Wood	1	Electric motor	1	19	6
2	II	Steel	1	Hydraulic motor	1	14	4
3	I	Steel	2	Electric motor	2	19	6

The first ACS prototype is expected to have a longer cycle time than others. The main reason for high cycle time is the manual process of alignment and connections. This problem can be solved by introducing advanced robotic technologies for alignment and connections. The level of automation to be adopted at each stage of construction should be based on the trade-off between time and cost of construction. The second ACS prototype, which follows automated top-down construction category II, has the least cycle time. There are two main reasons for the best cycle time. All column modules are connected simultaneously, and the hydraulic motor is faster than the electric motor. However, the second ACS prototype is too costly for a low-rise building construction. Even though ACS prototype one is the least expensive among all prototypes, it is far too preliminary for actual construction sites. That makes ACS prototype three a better option for an affordable construction method with reasonably good cycle time.

Table C.2 Comparison of ACS prototypes

ACS prototype	Average cycle time (minutes)	Level of automation	Weight of one lifting machine (kg)	Total weight of the prototype (kg)	Cost of one lifting machine (₹)	Total cost of the prototype (₹)
1	60	Lifting: automated; Connections: manual	16	100	31,666	190,000
2	2.65	Lifting: automated; Connection of beam modules: manual; Connection of column modules: automated	500	2000	600,000	2,400,000
3	16	Lifting: automated; Connections: manual	40	250	200,000	1,200,000

Comparing the ease of construction, ACS prototype two is the best option with the highest level of automation. The few human involvements in the construction are the loading of column modules and the connection of beam modules at the beginning of construction. These activities do not require high skill. This ACS prototype has an option to manually operate the construction system along with a fully automated operation cycle. The third ACS prototype involves the manual connection of column modules. This operation can also be performed by unskilled labour. The connections are relatively easier than that of ACS prototype one and any conventional construction methods. The connection of timber modules in ACS prototype one is by screwing and can be easily performed by unskilled workers. However, maintaining the level of the components requires some skill level.

The ACS prototype thee is lighter than ACS prototype two and the most compact while comparing individual machines. Even though ACS prototype one is the lightest among all prototypes, it is bulky. Transportation of this prototype is simple, but the initial set-up, assembling and disassembling require skilled labour. Transportation, assembling, and disassembling ACS prototype three are more effortless than ACS prototype two. The reason is that all of the six machines in ACS prototype three are light and compact. Each of these machines can be moved using a simple metal trolley. Setting up and dismantling the ACS at construction sites does not require any skilled labour. The individual machines in the second ACS prototype are heavy, bulky and contain numerous sensors. A skilled forklift operator is required for shifting and placing the ACS without damaging the sensors. The initial set-up of the machines and the final dismantling also require a well-trained operator.

Comparing the overall performances in each criterion, ACS prototype three is the best economical option for constructing low-rise buildings. While construction time is the governing criterion, ACS prototype two is the best option. In either case, further modification has to be made in the ACS prototypes to secure the sensors and better performance before implementing them on the actual construction site. Therefore, ACS prototype three is adopted for validating the monitoring framework proposed in this study.

REFERENCES

1. Ahn, C. R., Lee, S., Peña, F., *et al.* (2015) 'Application of Low-Cost Accelerometers for Measuring the Operational Efficiency of a Construction Equipment Fleet', *Journal of Computing in Civil Engineering*, 29(2), p. 04014042. doi: 10.1061/(ASCE)CP.1943.
2. Akhavian, R. and Behzadan, A. H. (2014) 'Construction activity recognition for simulation input modeling using machine learning classifiers', in *Proceedings of the Winter Simulation Conference 2014*. IEEE, pp. 3296–3307. doi: 10.1109/WSC.2014.7020164.
3. Akhavian, R. and Behzadan, A. H. (2015) 'Construction equipment activity recognition for simulation input modeling using mobile sensors and machine learning classifiers', *Advanced Engineering Informatics*, 29, pp. 867–877. doi: 10.1016/j.aei.2015.03.001.
4. Akhavian, R. and Behzadan, A. H. (2016) 'Smartphone-based construction workers' activity recognition and classification', *Automation in Construction*, 71(Part 2), pp. 198–209. doi: 10.1016/j.autcon.2016.08.015.
5. Akinosho, T. D., Oyedele, L. O., Bilal, M., *et al.* (2020) 'Deep Learning in the Construction Industry: A Review of Present Status and Future Innovations', *Journal of Building Engineering*, p. 101827. doi: 10.1016/j.jobe.2020.101827.
6. Alavi, A. H., Hasni, H., Lajnef, N., *et al.* (2016) 'Continuous health monitoring of pavement systems using smart sensing technology', *Construction and Building Materials*, 114, pp. 719–736. doi: 10.1016/j.conbuildmat.2016.03.128.
7. AlShorman, O., Alkahatni, F., Masadeh, M., *et al.* (2021) 'Sounds and acoustic emission-based early fault diagnosis of induction motor: A review study', *Advances in Mechanical Engineering*. SAGE Publications Inc. doi: 10.1177/1687814021996915.
8. Alshorman, O., Irfan, M., Saad, N., *et al.* (2020) 'A Review of Artificial Intelligence Methods for Condition Monitoring and Fault Diagnosis of Rolling Element Bearings for Induction Motor', *Shock and Vibration*, 2020, p. 8843759. doi: 10.1155/2020/8843759.
9. Amezquita-Sanchez, J. P. and Adeli, H. (2015) 'Synchrosqueezed wavelet transform-fractality model for locating, detecting, and quantifying damage in smart highrise building structures', *Smart Materials and Structures*, 24(6). doi: 10.1088/0964-1726/24/6/065034.
10. Arnesano, M., Revel, G. M. and Seri, F. (2016) 'A tool for the optimal sensor placement to optimize temperature monitoring in large sports spaces', *Automation in Construction*, 68, pp. 223–234. doi: 10.1016/j.autcon.2016.05.012.
11. Arras, L., Arjona-Medina, J., Widrich, M., *et al.* (2019) 'Explaining and Interpreting LSTMs', in *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. Springer Verlag, pp. 211–238. doi: 10.1007/978-3-030-28954-6_11.
12. Azar, E. R. (2016) 'Construction Equipment Identification Using Marker-Based Recognition and an Active Zoom Camera', *Journal of Computing in Civil Engineering*, 30(3), p. 04015033. doi: 10.1061/(ASCE)CP.1943-5487.0000507.

13. Bertola, N. J. and Smith, I. F. C. (2019) ‘A methodology for measurement-system design combining information from static and dynamic excitations for bridge load testing’, *Journal of Sound and Vibration*, p. 114953. doi: 10.1016/j.jsv.2019.114953.
14. Bishop, C. M. (2006) *Pattern Recognition And Machine Learning*. Edited by M. Jordan, J. Kleinberg, and B. Schölkopf. Singapore: Springer.
15. Bock, T. and Linner, T. (2015) *Robot-oriented design: Design and management tools for the deployment of automation and robotics in construction*. Cambridge University Press. doi: 10.1017/CBO9781139924146.
16. Bock, T. and Linner, T. (2016a) *Construction Robots: Elementary Technologies and Single-Task Construction Robots*, *Construction Robots*. New York: Cambridge University Press. doi: 10.1017/cbo9781139872041.
17. Bock, T. and Linner, T. (2016b) *Site Automation Automated/Robotic On-site Factories*. 1st edn. New York: Cambridge University Press.
18. Brownjohn, J. M. W. (2007) ‘Structural health monitoring of civil infrastructure’, *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 365(1851), pp. 589–622. doi: 10.1098/rsta.2006.1925.
19. Bureau of Labor Statistics (2018) *National census of fatal occupational injuries in 2017*. Available at: https://www.bls.gov/news.release/pdf/cfoi.pdf.
20. Bureau of Labor Statistics (2020) *National Census of Fatal Occupational Injuries in 2019*. Available at: www.bls.gov/iif (Accessed: 10 July 2021).
21. Cai, S., Ma, Z., Skibniewski, M. J., *et al.* (2019) ‘Construction automation and robotics for high-rise buildings over the past decades: A comprehensive review’, *Advanced Engineering Informatics*, 42, p. 100989. doi: 10.1016/J.AEI.2019.100989.
22. Cao, J., Huang, W., Zhao, T., *et al.* (2017) ‘An enhance excavation equipments classification algorithm based on acoustic spectrum dynamic feature’, *Multidimensional Systems and Signal Processing*, 28(3), pp. 921–943. doi: 10.1007/s11045-015-0374-z.
23. Cao, J., Wang, W., Wang, J., *et al.* (2017) ‘Excavation Equipment Recognition Based on Novel Acoustic Statistical Features’, *IEEE transactions on cybernetics*, 47(12), pp. 4392–4404. doi: 10.1109/TCYB.2016.2609999.
24. Cao, J., Zhao, T., Wang, J., *et al.* (2017) ‘Excavation equipment classification based on improved MFCC features and ELM’, *Neurocomputing*, 261, pp. 231–241. doi: 10.1016/j.neucom.2016.03.113.
25. Castro-Lacouture, D. (2009) ‘Construction Automation’, in Nof, S. Y. (ed.) *Springer Handbook of Automation*. Springer, pp. 1063–1078.
26. Chen, C., Zhu, Z. and Hammad, A. (2020) ‘Automated excavators activity recognition and productivity analysis from construction site surveillance videos’, *Automation in Construction*, 110, p. 103045. doi: 10.1016/j.autcon.2019.103045.
27. Chen, S., Ge, H., Li, H., *et al.* (2021) ‘Hierarchical deep convolution neural networks based on transfer learning for transformer rectifier unit fault diagnosis’, *Measurement: Journal of the International Measurement Confederation*, 167, p. 108257. doi: 10.1016/j.measurement.2020.108257.
28. Cheng, C.-F., Rashidi, A., Davenport, M. A., *et al.* (2017) ‘Activity analysis of construction equipment using audio signals and support vector machines’, *Automation in Construction*, 81, pp. 240–253. doi: 10.1016/J.AUTCON.2017.06.005.

29. Cheng, C. F., Rashidi, A., Davenport, M. A., *et al.* (2019) 'Evaluation of Software and Hardware Settings for Audio-Based Analysis of Construction Operations', *International Journal of Civil Engineering*, 17(9), pp. 1469–1480. doi: 10.1007/s40999-019-00409-2.
30. Chow, M. Y., Yee, S. O. and Mangum, P. M. (1991) 'A Neural Network Approach to Real-Time Condition Monitoring of Induction Motors', *IEEE Transactions on Industrial Electronics*, 38(6), pp. 448–453. doi: 10.1109/41.107100.
31. Ding, X., Guo, Y., Liu, T., *et al.* (2021) 'New fault diagnostic strategies for refrigerant charge fault in a VRF system using hybrid machine learning method', *Journal of Building Engineering*, 33, p. 101577. doi: 10.1016/j.jobe.2020.101577.
32. Ergen, E., Guven, G., Kurc, O., *et al.* (2015) 'Blockage assessment of buildings during emergency using multiple types of sensors', *Automation in Construction*, 49(PA), pp. 71–82. doi: 10.1016/j.autcon.2014.10.001.
33. Fard, M. G. (2021) *Real-Time and Automated Monitoring and Control Lab*. Available at: https://raamac.cee.illinois.edu/research-topics (Accessed: 18 December 2021).
34. Gangsar, P. and Tiwari, R. (2019) 'Online Diagnostics of Mechanical and Electrical Faults in Induction Motor Using Multiclass Support Vector Machine Algorithms Based on Frequency Domain Vibration and Current Signals', *ASCE-ASME Journal of Risk and Uncertainty in Engineering Systems, Part B: Mechanical Engineering*, 5(3). doi: 10.1115/1.4043268.
35. Gangsar, P. and Tiwari, R. (2020) 'Signal based condition monitoring techniques for fault detection and diagnosis of induction motors: A state-of-the-art review', *Mechanical Systems and Signal Processing*, 144, p. 106908. doi: 10.1016/j.ymssp.2020.106908.
36. Gassel, F. van (2005) 'The Development of a Concept for a Dutch Construction System for High-Rise Buildings', in *22nd International Symposium on Automation and Robotics in Construction (ISARC 2005)*. Ferrara,Italy, pp. 1–4. doi: 10.22260/ISARC2005/0042.
37. Gharsellaoui, S., Mansouri, M., Trabelsi, M., *et al.* (2020) 'Fault diagnosis of heating systems using multivariate feature extraction based machine learning classifiers', *Journal of Building Engineering*, 30, p. 101221. doi: 10.1016/j.jobe.2020.101221.
38. Golovina, O., Perschewski, M., Teizer, J., *et al.* (2019) 'Algorithm for quantitative analysis of close call events and personalized feedback in construction safety', *Automation in Construction*, 99, pp. 206–222. doi: 10.1016/j.autcon.2018.11.014.
39. Golparvar-Fard, M., Heydarian, A. and Niebles, J. C. (2013) 'Vision-based action recognition of earthmoving equipment using spatio-temporal features and support vector machine classifiers', *Advanced Engineering Informatics*, 27(4), pp. 652–663. doi: 10.1016/J.AEI.2013.09.001.
40. Golparvar-Fard, M., Peña-Mora, F., Arboleda, C. A., *et al.* (2009) 'Visualization of Construction Progress Monitoring with 4D Simulation Model Overlaid on Time-Lapsed Photographs', *Journal of Computing in Civil Engineering*, 23(6), pp. 391–404. doi: 10.1061/(ASCE)0887-3801(2009)23:6(391).
41. Gong, J., Caldas, C. H. and Gordon, C. (2011) 'Learning and classifying actions of construction workers and equipment using Bag-of-Video-Feature-Words and Bayesian network models', *Advanced Engineering Informatics*,

25(4), pp. 771–782. doi: 10.1016/j.aei.2011.06.002.
42. Goulet, J.-A. (2012) *Probabilistic Model Falsification for Infrastructure Diagnosis, Doctoral Thesis*, *Doctoral Thesis*. École Polytechnique Fédérale de Lausanne, Lausanne.
43. Goulet, J. A., Coutu, S. and Smith, I. F. C. C. (2013) 'Model falsification diagnosis and sensor placement for leak detection in pressurized pipe networks', *Advanced Engineering Informatics*, 27(2), pp. 261–269. doi: 10.1016/j.aei.2013.01.001.
44. Goulet, J. A. and Smith, I. F. C. (2013) 'Performance-Driven Measurement System Design for Structural Identification', *Journal of Computing in Civil Engineering*, 27(4), pp. 427–436. doi: 10.1061/(ASCE)CP.1943-5487.0000250.
45. Goyal, D., Vanraj, Pabla, B. S., *et al.* (2019) 'Non-contact sensor placement strategy for condition monitoring of rotating machine-elements', *Engineering Science and Technology, an International Journal*, 22(2), pp. 489–501. doi: 10.1016/j.jestch.2018.12.006.
46. Haidong, S., Junsheng, C., Hongkai, J., *et al.* (2020) 'Enhanced deep gated recurrent unit and complex wavelet packet energy moment entropy for early fault prognosis of bearing', *Knowledge-Based Systems*, 188, p. 105022. doi: 10.1016/j.knosys.2019.105022.
47. Hamada, K., Furuya, N., Inoue, Y., *et al.* (1998) 'Development of automated construction system for high-rise reinforced concrete buildings', in *IEEE International Conference on Robotics and Automation*. Leuven, Belgium: IEEE, pp. 2428–2433. doi: 10.1109/ROBOT.1998.680704.
48. Haniš, T. and Hromčík, M. (2011) 'Information-based sensor placement optimization for BWB aircraft', *IFAC Proceedings Volumes*, 44(1), pp. 2236–2241. doi: 10.3182/20110828-6-IT-1002.00428.
49. Harichandran, A., Raphael, B. and Mukherjee, A. (2019a) 'Determination of Automated Construction Operations from Sensor Data Using Machine Learning', in *4th International Conference on Civil and Building Engineering Informatics*. Sendai, Japan, pp. 77–84.
50. Harichandran, A., Raphael, B. and Mukherjee, A. (2019b) 'Identification of the Structural State in Automated Modular Construction', in *36th International Symposium on Automation and Robotics in Construction (ISARC 2019)*. Banff, Canada, pp. 187–193. doi: https://doi.org/10.22260/ISARC2019/0026.
51. Harichandran, A., Raphael, B. and Mukherjee, A. (2020a) 'A Robust Framework for Identifying Automated Construction Operations', in *37th International Symposium on Automation and Robotics in Construction (ISARC 2020)*. Kitakyushu, Japan, pp. 473–480. doi: https://doi.org/10.22260/ISARC2020/0066.
52. Harichandran, A., Raphael, B. and Mukherjee, A. (2020b) 'Development of Automated Top-Down Construction System for Low-rise Building Structures', *International journal of industrialized construction*, 1(1), pp. 22–33. doi: doi.org/10.29173/ijic217.
53. Harichandran, A., Raphael, B. and Mukherjee, A. (2021) 'A hierarchical machine learning framework for the identification of automated construction operations', *Journal of Information Technology in Construction*, 26, pp. 591–623. doi: 10.36680/j.itcon.2021.031.
54. Harichandran, A., Raphael, B. and Varghese, K. (2018) 'Inferring Construction Activities from Structural Responses Using Support Vector

Machines', in *35th International Symposium on Automation and Robotics in Construction (ISARC 2018)*. Berlin, pp. 332–339. doi: https://doi.org/10.22260/ISARC2018/0047.
55. Hasni, H., Jiao, P., Alavi, A. H., *et al.* (2018) 'Structural health monitoring of steel frames using a network of self-powered strain and acceleration sensors: A numerical study', *Automation in Construction*, 85, pp. 344–357. doi: 10.1016/j.autcon.2017.10.022.
56. HBM (2020) *catman Data Acquisition Software*, *HBM*. Available at: https://www.hbm.com/en/2290/catman-data-acquisition-software/ (Accessed: 7 September 2020).
57. Hochreiter, S. (1998) 'The vanishing gradient problem during learning recurrent neural nets and problem solutions', *International Journal of Uncertainty, Fuzziness and Knowlege-Based Systems*, 6(2), pp. 107–116. doi: 10.1142/S0218488598000094.
58. Hochreiter, S. and Schmidhuber, J. (1996) 'LSTM can solve hard long time lag problems', in *Proceedings of the 9th International Conference on Neural Information Processing Systems (NIPS'96)*, pp. 473–479. Available at: https://dl.acm.org/doi/10.5555/2998981.2999048 (Accessed: 25 February 2021).
59. Hochreiter, S. and Schmidhuber, J. (1997) 'Long Short-Term Memory', *Neural Computation*, 9(8), pp. 1735–1780. doi: 10.1162/neco.1997.9.8.1735.
60. Hu, Z., Chen, W., Shen, D., *et al.* (2021) 'Optimal sensor placement for contamination identification in water distribution system considering contamination probability variations', *Computers & Chemical Engineering*, 153, p. 107404. doi: 10.1016/J.COMPCHEMENG.2021.107404.
61. Ikeda, Y. and Harada, T. (2006) 'Application of the Automated Building Construction System Using the Conventional Construction Method Together', in *23nd International Symposium on Automation and Robotics in Construction (ISARC 2006)*. Tokyo, Japan, pp. 722–727. doi: 10.22260/ISARC2006/0134.
62. Janssens, O., Van De Walle, R., Loccufier, M., *et al.* (2018) 'Deep Learning for Infrared Thermal Image Based Machine Health Monitoring', *IEEE/ASME Transactions on Mechatronics*, 23(1), pp. 151–159. doi: 10.1109/TMECH.2017.2722479.
63. Jayaswal, P., Wadhwani, A. K. and Mulchandani, K. B. (2008) 'Machine fault signature analysis', *International Journal of Rotating Machinery*, 2008, p. 583982. doi: 10.1155/2008/583982.
64. Jiang, X. and Adeli, H. (2007) 'Pseudospectra, MUSIC, and dynamic wavelet neural network for damage detection of highrise buildings', *International Journal for Numerical Methods in Engineering*, 71(5), pp. 606–629. doi: 10.1002/nme.1964.
65. Jiao, J., Zhao, M., Lin, J., *et al.* (2019) 'Hierarchical discriminating sparse coding for weak fault feature extraction of rolling bearings', *Reliability Engineering and System Safety*, 184, pp. 41–54. doi: 10.1016/j.ress.2018.02.010.
66. Jiao, J., Zhao, M., Lin, J., *et al.* (2020) 'A comprehensive review on convolutional neural network in machine fault diagnosis', *Neurocomputing*, 417, pp. 36–63. doi: 10.1016/j.neucom.2020.07.088.
67. Joshua, L. and Varghese, K. (2013) 'Selection of Accelerometer Location on Bricklayers Using Decision Trees', *Computer-Aided Civil and Infrastructure Engineering*, 28(5), pp. 372–388. doi: 10.1111/mice.12002.
68. Joshua, L. and Varghese, K. (2014) 'Automated recognition of construction

labour activity using accelerometers in field situations', *International Journal of Productivity and Performance Management*, 63(7), pp. 841–862. doi: 10.1108/IJPPM-05-2013-0099.

69. Júnior, A. M. G., Silva, V. V. R., Baccarini, L. M. R., *et al.* (2018) 'The design of multiple linear regression models using a genetic algorithm to diagnose initial short-circuit faults in 3-phase induction motors', *Applied Soft Computing Journal*, 63, pp. 50–58. doi: 10.1016/j.asoc.2017.11.015.
70. Kang, T.-K., Nam, C., Lee, U.-K., *et al.* (2011) 'Development of Robotic-Crane Based Automatic Construction System for Steel Structures of High-Rise Buildings', in *28th International Symposium on Automation and Robotics in Construction (ISARC 2011)*. Seoul, Korea, pp. 670–671. doi: 10.22260/ISARC2011/0125.
71. Kargul, A., Glaese, A., Kessler, S., *et al.* (2017) 'Heavy Equipment Demand Prediction with Support Vector Machine Regression Towards a Strategic Equipment Management', *International Journal of Structural and Civil Engineering Research*, 6(2), pp. 137–143. doi: 10.18178/ijscer.6.2.137-143.
72. Kazemian, A., Yuan, X., Davtalab, O., *et al.* (2019) 'Computer vision for real-time extrusion quality monitoring and control in robotic construction', *Automation in Construction*, 101, pp. 92–98. doi: 10.1016/J.AUTCON.2019.01.022.
73. Kim, Hyunsoo, Ahn, C. R., Engelhaupt, D., *et al.* (2018) 'Application of dynamic time warping to the recognition of mixed equipment activities in cycle time measurement', *Automation in Construction*, 87, pp. 225–234. doi: 10.1016/J.AUTCON.2017.12.014.
74. Kim, H., Anderson, K., Lee, S., *et al.* (2013) 'Generating construction schedules through automatic data extraction using open BIM (building information modeling) technology', *Automation in Construction*, 35, pp. 285–295. doi: 10.1016/j.autcon.2013.05.020.
75. Kim, Hongjo, Kim, Hyoungkwan, Hong, Y. W., *et al.* (2018) 'Detecting Construction Equipment Using a Region-Based Fully Convolutional Network and Transfer Learning', *Journal of Computing in Civil Engineering*, 32(2), p. 04017082. doi: 10.1061/(ASCE)CP.1943-5487.0000731.
76. Kim, J. and Chi, S. (2019) 'Action recognition of earthmoving excavators based on sequential pattern analysis of visual features and operation cycles', *Automation in Construction*, 104, pp. 255–264. doi: 10.1016/j.autcon.2019.03.025.
77. Kim, J., Chi, S. and Choi, M. (2019) 'Sequential Pattern Learning of Visual Features and Operation Cycles for Vision-Based Action Recognition of Earthmoving Excavators', in *Computing in Civil Engineering 2019: Data, Sensing, and Analytics - Selected Papers from the ASCE International Conference on Computing in Civil Engineering 2019*. American Society of Civil Engineers (ASCE), pp. 298–304. doi: 10.1061/9780784482438.038.
78. Kim, J., Chi, S. and Seo, J. (2018) 'Interaction analysis for vision-based activity identification of earthmoving excavators and dump trucks', *Automation in Construction*, 87, pp. 297–308. doi: 10.1016/j.autcon.2017.12.016.
79. Kim, K. and Cho, Y. K. (2020) 'Effective inertial sensor quantity and locations on a body for deep learning-based worker's motion recognition', *Automation in Construction*, 113, p. 103126. doi: 10.1016/j.autcon.2020.103126.
80. Kripakaran, P., Ravindran, S., Saitta, S., *et al.* (2007) 'Measurement system design using damage scenarios', in *ASCE International Workshop on*

Computing in Civil Engineering. Pittsburgh, USA, pp. 615–623. doi: 10.1061/40937(261)73.

81. Kripakaran, P., Saitta, S., Ravindran, S., *et al.* (2007) 'Optimal sensor placement for damage detection: Role of global search', in *Proceedings - International Workshop on Database and Expert Systems Applications, DEXA*, pp. 302–306. doi: 10.1109/DEXA.2007.35.
82. Kripakaran, P. and Smith, I. F. C. (2009) 'Configuring and enhancing measurement systems for damage identification', *Advanced Engineering Informatics*, 23, pp. 424–432. Available at: http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.615.7950&rep=rep1&type=pdf (Accessed: 11 October 2018).
83. Labrador Rivas, A. E. and Abrão, T. (2020) 'Faults in smart grid systems: Monitoring, detection and classification', *Electric Power Systems Research*, 189, p. 106602. doi: 10.1016/j.epsr.2020.106602.
84. Laguarta, J., Hueto, F. and Subirana, B. (2020) 'COVID-19 Artificial Intelligence Diagnosis Using Only Cough Recordings', *IEEE Open Journal of Engineering in Medicine and Biology*, 1, pp. 275–281. doi: 10.1109/OJEMB.2020.3026928.
85. Lakhal, O., Melingui, A., Dherbomez, G., *et al.* (2019) 'Control of a Hyper-Redundant Robot for Quality Inspection in Additive Manufacturing for Construction', in *2nd IEEE International Conference on Soft Robotics (RoboSoft)*. IEEE, pp. 448–453. doi: 10.1109/ROBOSOFT.2019.8722720.
86. Langroodi, A. K., Vahdatikhaki, F. and Doree, A. (2021) 'Activity recognition of construction equipment using fractional random forest', *Automation in Construction*, 122, p. 103465. doi: 10.1016/j.autcon.2020.103465.
87. Lashkari, N., Poshtan, J. and Azgomi, H. F. (2015) 'Simulative and experimental investigation on stator winding turn and unbalanced supply voltage fault diagnosis in induction motors using Artificial Neural Networks', *ISA Transactions*, 59, pp. 334–342. doi: 10.1016/j.isatra.2015.08.001.
88. Lei, Y., Lin, J., Zuo, M. J., *et al.* (2014) 'Condition monitoring and fault diagnosis of planetary gearboxes: A review', *Measurement: Journal of the International Measurement Confederation*, 48(1), pp. 292–305. doi: 10.1016/j.measurement.2013.11.012.
89. Lemke, S., Heizmann, A. and Kearney, T. (2019) 'Implementation of Automation and Digitization in Tunnel Waterproofing and Grouting Practices', in Hebert, C. D. and Hoffman, S. W. (eds) *Rapid Excavation and Tunneling Conference*. Chicago: Society for Mining, Metallurgy, and Exploration (SME), pp. 817–827.
90. Li, F. (2011) *Dynamic Modeling, Sensor Placement Design, and Fault Diagnosis of Nuclear Desalination Systems*. University of Tennessee, Knoxville. Available at: https://trace.tennessee.edu/utk_graddiss/991 (Accessed: 2 July 2019).
91. Li, G., Hu, Y., Liu, J., *et al.* (2021) 'Review on Fault Detection and Diagnosis Feature Engineering in Building Heating, Ventilation, Air Conditioning and Refrigeration Systems', *IEEE Access*, 9, pp. 2153–2187. doi: 10.1109/ACCESS.2020.3040980.
92. Li, J. (2021) 'Exploring the potential of utilizing unsupervised machine learning for urban drainage sensor placement under future rainfall uncertainty', *Journal of Environmental Management*, 296, p. 113191. doi: 10.1016/J.JENVMAN.2021.113191.
93. Liang, K., Zhao, M., Lin, J., *et al.* (2020) 'An information-based K-singular-

value decomposition method for rolling element bearing diagnosis', *ISA Transactions*, 96, pp. 444–456. doi: 10.1016/j.isatra.2019.06.012.

94. Lin, Z. H., Chen, A. Y. and Hsieh, S. H. (2021) 'Temporal image analytics for abnormal construction activity identification', *Automation in Construction*, 124, p. 103572. doi: 10.1016/j.autcon.2021.103572.
95. Liu, H. and Zhang, Y. (2019) 'Image-driven structural steel damage condition assessment method using deep learning algorithm', *Measurement*, 133, pp. 168–181. doi: 10.1016/j.measurement.2018.09.081.
96. Luo, X., Li, ; Heng, Cao, D., *et al.* (2018) 'Recognizing Diverse Construction Activities in Site Images via Relevance Networks of Construction-Related Objects Detected by Convolutional Neural Networks'. doi: 10.1061/(ASCE)CP.1943-5487.0000756.
97. Lyons, G. M., Culhane, K. M., Hilton, D., *et al.* (2005) 'A description of an accelerometer-based mobility monitoring technique', *Medical Engineering & Physics*, 27(6), pp. 497–504. doi: 10.1016/J.MEDENGPHY.2004.11.006.
98. Mahami, H., Nasirzadeh, F., Hosseininaveh Ahmadabadian, A., *et al.* (2019) 'Imaging network design to improve the automated construction progress monitoring process', *Construction Innovation*, 19(3), pp. 386–404. doi: 10.1108/CI-07-2018-0059.
99. Mahjoubi, S., Barhemat, R. and Bao, Y. (2020) 'Optimal placement of triaxial accelerometers using hypotrochoid spiral optimization algorithm for automated monitoring of high-rise buildings', *Automation in Construction*, 118. doi: 10.1016/j.autcon.2020.103273.
100. MATLAB & Simulink (2021) *Long Short-Term Memory Networks*. Available at: https://in.mathworks.com/help/deeplearning/ug/long-short-term-memory-networks.html#mw_0862a318-9d89-4952-8803-7b529c62214e (Accessed: 5 September 2021).
101. Matzka, S. (2020a) *AI4I 2020 Predictive Maintenance Dataset Data Set, UCI Machine Learning Repository, University of California, Irvine, School of Information and Computer Sciences*. Available at: https://archive.ics.uci.edu/ml/datasets/AI4I+2020+Predictive+Maintenance+Dataset (Accessed: 22 May 2021).
102. Matzka, S. (2020b) 'Explainable Artificial Intelligence for Predictive Maintenance Applications', in *3rd International Conference on Artificial Intelligence for Industries (AI4I 2020)*. Institute of Electrical and Electronics Engineers Inc., pp. 69–74. doi: 10.1109/AI4I49448.2020.00023.
103. Melenbrink, N., Werfel, J. and Menges, A. (2020) 'On-site autonomous construction robots: Towards unsupervised building', *Automation in Construction*, 119, p. 103312. doi: 10.1016/j.autcon.2020.103312.
104. Men, X. and Zhang, X. (2019) 'Case Study Analysis for Development Strategies of Construction 3D Printing', in *International Conference on Applied Human Factors and Ergonomics (AHFE 2019)*. Washington D.C., USA, pp. 439–450. doi: 10.1007/978-3-030-20216-3_41.
105. Mitchell, T. M. (1997) *Machine Learning*. McGraw-Hill Education.
106. Mobed, P., Pednekar, P., Bhattacharyya, D., *et al.* (2016) *Model-Based Sensor Placement for Component Condition Monitoring and Fault Diagnosis in Fossil Energy Systems*. Available at: https://www.osti.gov/servlets/purl/1351548 (Accessed: 2 July 2019).
107. Molnar, V., Fedorko, G., Honus, S., *et al.* (2020) 'Research in placement of measuring sensors on hexagonal idler housing with regard to requirements of pipe conveyor failure analysis', *Engineering Failure Analysis*, 116, p. 104703.

doi: 10.1016/j.engfailanal.2020.104703.
108. do Nascimento, F. A. L., da Silva, A. J. P., de Freitas, F. T. O., *et al.* (2021) ‘Sensor placement in 2D/3D wetting patterns from drip irrigation for quantification of evapotranspiration’, *Computers and Electronics in Agriculture*, 188, p. 106356. doi: 10.1016/J.COMPAG.2021.106356.
109. Netti, A., Kiziltan, Z., Babaoglu, O., *et al.* (2020) ‘A machine learning approach to online fault classification in HPC systems’, *Future Generation Computer Systems*, 110, pp. 1009–1022. doi: 10.1016/j.future.2019.11.029.
110. Nguyen, N. T. and Lee, H. H. (2008) ‘An application of support vector machines for induction motor fault diagnosis with using genetic algorithm’, in *Lecture Notes in Computer Science*. Berlin, Heidelberg: Springer, pp. 190–200. doi: 10.1007/978-3-540-85984-0_24.
111. Pachón, P., Infantes, M., Cámara, M., *et al.* (2020) ‘Evaluation of optimal sensor placement algorithms for the Structural Health Monitoring of architectural heritage. Application to the Monastery of San Jerónimo de Buenavista (Seville, Spain)’, *Engineering Structures*, 202. doi: 10.1016/j.engstruct.2019.109843.
112. Pang, G., Shen, C., Cao, L., *et al.* (2021) ‘Deep Learning for Anomaly Detection: A Review’, *ACM Computing Surveys*, 54(2), p. 38. doi: 10.1145/3439950.
113. Papadopoulou, M., Raphael, B., Smith, I. F. C., *et al.* (2014) ‘Hierarchical sensor placement using joint entropy and the effect of modeling error’, *Entropy*, 16(9), pp. 5078–5101. doi: 10.3390/e16095078.
114. Papadopoulou, M., Raphael, B., Smith, I. F. C., *et al.* (2016) ‘Optimal Sensor Placement for Time-Dependent Systems: Application to Wind Studies around Buildings’, *Journal of Computing in Civil Engineering*, 30(2), pp. 1–14. doi: 10.1061/(ASCE)CP.1943-5487.0000497.
115. Park, J., Kim, K. and Cho, Y. K. (2017) ‘Framework of Automated Construction-Safety Monitoring Using Cloud-Enabled BIM and BLE Mobile Tracking Sensors’, *Journal of Construction Engineering and Management*, 143(2), p. 05016019. doi: 10.1061/(ASCE)CO.1943-7862.0001223.
116. Pu, Y., Szmigiel, A., Chen, J., *et al.* (2020) ‘FlotationNet: A hierarchical deep learning network for froth flotation recovery prediction’, *Powder Technology*, 375, pp. 317–326. doi: 10.1016/j.powtec.2020.07.102.
117. Quatrini, E., Costantino, F., Di Gravio, G., *et al.* (2020) ‘Machine learning for anomaly detection and process phase classification to improve safety and maintenance activities’, *Journal of Manufacturing Systems*, 56, pp. 117–132. doi: 10.1016/j.jmsy.2020.05.013.
118. Radlov, K. and Ivanov, G. (2020) ‘Analysis of accidents with tower cranes on construction sites and recommendations for their prevention’, in *IOP Conference Series: Materials Science and Engineering*. IOP Publishing Ltd. doi: 10.1088/1757-899X/951/1/012025.
119. Rafiei, M. H. and Adeli, H. (2017) ‘A novel machine learning-based algorithm to detect damage in high-rise building structures’, *Structural Design of Tall and Special Buildings*, 26(18), p. e1400. doi: 10.1002/tal.1400.
120. Rajeswaran, N., Lakshmi Swarupa, M., Sanjeeva Rao, T., *et al.* (2018) ‘Hybrid Artificial Intelligence based Fault Diagnosis of SVPWM Voltage Source Inverters for Induction Motor’, in *Materials Today: Proceedings*. Elsevier Ltd, pp. 565–571. doi: 10.1016/j.matpr.2017.11.119.
121. Raphael, B. and Harichandran, A. (2020) ‘Sensor Data Interpretation in Bridge Monitoring—A Case Study’, *Frontiers in Built Environment*, 5, p. 148. doi:

10.3389/fbuil.2019.00148.
122. Raphael, B., Rao, K. S. C. and Varghese, K. (2016) ‘Automation of modular assembly of structural frames for buildings’, in *33rd International Symposium on Automation and Robotics in Construction (ISARC 2016)*. Auburn, USA, pp. 412–420. doi: https://doi.org/10.22260/ISARC2016/0050.
123. Rashid, K. M. and Louis, J. (2019) ‘Times-series data augmentation and deep learning for construction equipment activity recognition’, *Advanced Engineering Informatics*, 42, p. 100944. doi: 10.1016/j.aei.2019.100944.
124. Rashid, K. M. and Louis, J. (2020) ‘Activity identification in modular construction using audio signals and machine learning’, *Automation in Construction*, 119, p. 103361. doi: 10.1016/j.autcon.2020.103361.
125. Robert-Nicoud, Y., Raphael, B. and Smith, I. F. C. (2005) ‘Configuration of measurement systems using Shannon’s entropy function’, *Computers and Structures*, 83(8–9), pp. 599–612. doi: 10.1016/j.compstruc.2004.11.007.
126. Roberts, D. and Golparvar-Fard, M. (2019) ‘End-to-end vision-based detection, tracking and activity analysis of earthmoving equipment filmed at ground level’, *Automation in Construction*, 105, p. 102811. doi: 10.1016/j.autcon.2019.04.006.
127. Sabillon, C. A., Rashidi, A., Samanta, B., *et al.* (2018) ‘A productivity forecasting system for construction cyclic operations using audio signals and a Bayesian approach’, in *Construction Research Congress 2018*. American Society of Civil Engineers (ASCE), pp. 295–304. doi: 10.1061/9780784481264.029.
128. Sacks, R., Navon, R., Shapira, A., *et al.* (2002) ‘Monitoring Construction Equipment for Automated Project Performance Control’, in *Proceedings of the 19th International Symposium on Automation and Robotics in Construction (ISARC)*. Washington, USA, pp. 161–166. doi: https://doi.org/10.22260/ISARC2002/0025.
129. De Santis, E., Rizzi, A. and Sadeghian, A. (2018) ‘A cluster-based dissimilarity learning approach for localized fault classification in Smart Grids’, *Swarm and Evolutionary Computation*, 39, pp. 267–278. doi: 10.1016/j.swevo.2017.10.007.
130. Sekiguchi, T., Honma, K., Mizutani, R., *et al.* (1997) ‘The Development and Application of an Automatic Building Construction System Using Push-Up Machines’, in *Proceedings of the 14th International Symposium on Automation and Robotics in Construction (ISARC)*. Pittsburgh, USA: International Association for Automation and Robotics in Construction (IAARC), pp. 321–328. doi: 10.22260/isarc1997/0040.
131. Shalev-Shwartz, S. and Ben-David, S. (2014) *Understanding Machine Learning: From Theory to Algorithms*. 1st edn. New York: Cambridge University Press.
132. Shannon, C. E. (1948) ‘A Mathematical Theory of Communication’, *Bell System Technical Journal*, 27, pp. 379–423, 623–656. doi: 10.1002/j.1538-7305.1948.tb01338.x.
133. Shannon, C. and Weaver, W. (1964) *The Mathematical Theory of Communication*. Urbana, USA: The University of Illinois Press.
134. Shao, S. Y., Sun, W. J., Yan, R. Q., *et al.* (2017) ‘A Deep Learning Approach for Fault Diagnosis of Induction Motors in Manufacturing’, *Chinese Journal of Mechanical Engineering (English Edition)*, 30(6), pp. 1347–1356. doi: 10.1007/s10033-017-0189-y.
135. Sharma, H., Vaidya, U. and Ganapathysubramanian, B. (2019) ‘A transfer

operator methodology for optimal sensor placement accounting for uncertainty', *Building and Environment*, 155, pp. 334–349. doi: 10.1016/j.buildenv.2019.03.054.

136. Sheikhkhoshkar, M., Pour Rahimian, F., Kaveh, M. H., *et al.* (2019) 'Automated planning of concrete joint layouts with 4D-BIM', *Automation in Construction*, 107, p. 102943. doi: 10.1016/j.autcon.2019.102943.
137. Sherafat, B., Ahn, C. R., Akhavian, R., *et al.* (2020) 'Automated Methods for Activity Recognition of Construction Workers and Equipment: State-of-the-Art Review', *Journal of Construction Engineering and Management*, 146(6), p. 03120002. doi: 10.1061/(ASCE)CO.1943-7862.0001843.
138. Shi, Y., Xia, Y., Zhang, Y., *et al.* (2020) 'Intelligent identification for working-cycle stages of excavator based on main pump pressure', *Automation in Construction*, 109, p. 102991. doi: 10.1016/j.autcon.2019.102991.
139. Slaton, T., Hernandez, C. and Akhavian, R. (2020) 'Construction activity recognition with convolutional recurrent networks', *Automation in Construction*, 113, p. 103138. doi: 10.1016/j.autcon.2020.103138.
140. Soman, R. K., Raphael, B. and Varghese, K. (2015) 'Sensor placement to monitor launching girder operations in segmental construction', in *32nd International Symposium on Automation and Robotics in Construction and Mining*. Oulu, Finland.
141. Soman, R. K., Raphael, B. and Varghese, K. (2017) 'A System Identification Methodology to monitor construction activities using structural responses', *Automation in Construction*, 75, pp. 79–90. doi: 10.1016/j.autcon.2016.12.006.
142. Stahel, W. and Maechler, M. (2021) *R: 'Jitter' (Add Noise) to Numbers*. Available at: https://stat.ethz.ch/R-manual/R-patched/library/base/html/jitter.html (Accessed: 19 June 2021).
143. Sun, W., Shao, S., Zhao, R., *et al.* (2016) 'A sparse auto-encoder-based deep neural network approach for induction motor faults classification', *Measurement*, 89, pp. 171–178. doi: 10.1016/j.measurement.2016.04.007.
144. Tamayo, E. C., Khan, Y. I., Qureshi, A. J., *et al.* (2018) 'Design automation of control panels for automated modular construction machines', *Procedia CIRP*, 70, pp. 404–409. doi: 10.1016/j.procir.2018.02.004.
145. Tanijiri, H., Ishiguro, B., Arai, T., *et al.* (1997) 'Development of automated weather-unaffected building construction system', *Automation in Construction*, 6(3), pp. 215–227. doi: 10.1016/S0926-5805(97)00005-8.
146. Valero, E., Forster, A., Bosché, F., *et al.* (2019) 'Automated defect detection and classification in ashlar masonry walls using machine learning', *Automation in Construction*, 106, p. 102846. doi: 10.1016/j.autcon.2019.102846.
147. Wakisaka, T., Furuya, N., Inoue, Y., *et al.* (2000) 'Automated construction system for high-rise reinforced concrete buildings', *Automation in Construction*, 9(3), pp. 229–250. doi: 10.1016/S0926-5805(99)00039-4.
148. Wang, D., Chen, J., Zhao, D., *et al.* (2017) 'Monitoring workers ' attention and vigilance in construction activities through a wireless and wearable electroencephalography system', *Automation in Construction*, 82, pp. 122–137. doi: 10.1016/j.autcon.2017.02.001.
149. Wang, Z. and Azar, E. R. (2019) 'BIM-based draft schedule generation in reinforced concrete-framed buildings', *Construction Innovation*, 19(2), pp. 280–294. doi: 10.1108/CI-11-2018-0094.
150. Xing, L., Raviv, T. and Sela, L. (2022) 'Sensor placement for robust burst

identification in water systems: Balancing modeling accuracy, parsimony, and uncertainties', *Advanced Engineering Informatics*, 51, p. 101484. doi: 10.1016/J.AEI.2021.101484.

151. Xu, Z., Guo, Y. and Homer Saleh, J. (2022) 'Multi-objective optimization for sensor placement: An integrated combinatorial approach with reduced order model and Gaussian process', *Measurement*, 187, p. 110370. doi: 10.1016/J.MEASUREMENT.2021.110370.
152. Xu, Z. and Saleh, J. H. (2021) 'Machine learning for reliability engineering and safety applications: Review of current status and future opportunities', *Reliability Engineering and System Safety*. arXiv, p. 107530. doi: 10.1016/j.ress.2021.107530.
153. Yamazaki, Y. and Maeda, J. (1998) 'The SMART system: an integrated application of automation and information technology in production process', *Computers in Industry*, 35(1), pp. 87–99. doi: 10.1016/S0166-3615(97)00086-9.
154. Yang, C., Liang, K. and Zhang, X. (2020) 'Strategy for sensor number determination and placement optimization with incomplete information based on interval possibility model and clustering avoidance distribution index', *Computer Methods in Applied Mechanics and Engineering*, 366. doi: 10.1016/j.cma.2020.113042.
155. Yang, C., Zheng, W. and Zhang, X. (2019) 'Optimal sensor placement for spatial lattice structure based on three-dimensional redundancy elimination model', *Applied Mathematical Modelling*, 66, pp. 576–591. doi: 10.1016/j.apm.2018.09.034.
156. Yang, K. and Ahn, C. R. (2019) 'Inferring workplace safety hazards from the spatial patterns of workers' wearable data', *Advanced Engineering Informatics*, 41, p. 100924. doi: 10.1016/j.aei.2019.100924.
157. Yang, W., Yang, H. and Tang, S. (2019) 'Optimization and control application of sensor placement in aeroservoelastic of UAV', *Aerospace Science and Technology*, 85, pp. 61–74. doi: 10.1016/J.AST.2018.11.050.
158. Yu, J., Zavala, V. M. and Anitescu, M. (2018) 'A scalable design of experiments framework for optimal sensor placement', *Journal of Process Control*, 67, pp. 44–55. doi: 10.1016/j.jprocont.2017.03.011.
159. Yu, M., Wang, D. and Luo, M. (2014) 'Model-based prognosis for hybrid systems with mode-dependent degradation behaviors', *IEEE Transactions on Industrial Electronics*, 61(1), pp. 546–554. doi: 10.1109/TIE.2013.2244538.
160. Zhong, D., Li, X., Cui, B., *et al.* (2018) 'Technology and application of real-time compaction quality monitoring for earth-rockfill dam construction in deep narrow valley', *Automation in Construction*, 90, pp. 23–38. doi: 10.1016/J.AUTCON.2018.02.024.

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APPENDIX D

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3 messages

Aparna Harichandran <aparnaharichandran@gmail.com> 18 December 2021 at 23:03
To: cupkol@cambridge.org, thomas.bock@br2.ar.tum.de, thomas.linner@br2.ar.tum.de

Dear Sir/Madam,

I am a final year doctoral degree candidate at Indian Institute of Technology Madras, India. My area of research is construction automation.
The concept related to high-rise automated construction systems needs to be described in the literature review chapter of my PhD thesis.
Two of the figures from the book titled **'Site Automation, Automated/Robotic On-site Factories'** (ISBN 9781107075979) by Thomas Bock and Thomas Linner will be helpful for the description.
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Looking forward to hearing from you.

Kind regards,
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Dear Aparna Harichandran,

from side of me and Prof. Bock it is fine, please reference it properly to our book.

All the best for you thesis!

Kind regards,

Thomas Linner

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Aparna Harichandran <aparnaharichandran@gmail.com> 19 December 2021 at 08:25
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