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INSOLVENCY PREDICTION OF AUSTRALIAN CONSTRUCTION COMPANIES USING DEEP LEARNING WITH BIDIRECTIONAL LSTM AUTOENCODER

Lishan Bu[1], Shaoli Wang[2], Gang Lin[1] and Honglei Xu[*1]

[1]School of Electrical Engineering Computing and Mathematical Sciences
Curtin University, Australia

[2]School of Design and the Built Environment, Curtin University, Australia

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Abstract. Business insolvency in the building and construction industry is a major concern on a worldwide scale, and it is particularly pervasive in the Australian construction industry. Many Australian construction companies frequently uses high levels of borrowing and poor profit margins, which increases the likelihood of insolvency. This paper develops a novel, intelligent insolvency prediction model for the Australian construction companies. The proposed framework with bidirectional long short-term memory (BiLSTM) models and autoencoder techniques contains not only the financial variables but also other important indicators that are linked to the features of the sector that have previously been disregarded. Finally, numerical experiments show that the proposed neural network model outperforms several existing models for predicting the insolvency of construction companies.

1. **Introduction.** Due to its high sensitivity to the economy and the nature of the lengthy project lifecycle, construction has always been one of the most challenging and risky industries globally, particularly in Australia. Increased market demand during the rise in the economy leads to a shortage of contractors and supplies, higher building costs, and unavoidable staff alterations. To adapt to the market change, businesses must hire more employees and bear higher overhead costs. When there aren't enough projects available on the market, job numbers and profit margins decline even though company overhead stays essentially the same. The market has excessive competition because the entry barriers are relatively low. Companies are offering low prices in order to win contracts and cover their overhead costs, but in the end, they are likely to experience a loss, which can cause them to become insolvent and destroy the health of the market. Compared to other sectors, construction industry's various peculiarities and sensitivities increase the vulnerability, making Australian construction and building companies face significant operational and financial risk [15, 16].

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[*]Corresponding author: Honglei Xu.

Failure of a construction company has a significant impact on society and other construction companies in addition to causing significant losses to the company owners, employees, shareholders, customers, and contractors. The business suffers the loss of profit, assets, and reputation; employees lose their jobs, which could have a significant negative impact on their families; customers, developers, and homeowners are left with unfinished or delayed projects; and unpaid contractors in the project chain may go bankrupt and have an adverse effect on their other contracted building companies. Therefore, for several decades, both researchers and practitioners have been interested in the topic of predicting company insolvency [11,16,20], which motivates our research.

This paper proposes a stacked neural network framework with BiLSTM and autoencoder techniques to predict the insolvency of Australian construction companies. The research explores and evaluates not only the financial aspects but a broader factors that tend to be neglected in the past such as management factors, macroeconomic factors and the characteristics of the Australian construction industry. The proposed prediction model establishes the relationship between these factors and construction company insolvency.

The reminder of the paper is organised as follows: Section 2 reviews the recent research on business insolvency prediction by neural networks. In Section 3, we develop the proposed framework with BiLSTM models and autoencoder techniques. Section 4 compares the proposed model's results with those of LSTM models, BiLSTM models and CNN-BiLSTM (convolutional neural network bidirectional long short-term memory) models and Section 5 concludes this paper.

2. **Literature review.**

Traditional business insolvency prediction usually relies on statistical analysis [2–4,6,23,26] . In the late 20th century, machine learning (ML) techniques started to be used to predict business failure as computer technology advanced. Decision trees, neural networks, support vector machines, and random forests have all been widely utilized among these techniques. For instance, some scholars have demonstrated that the ML model outperformed traditional statistical models in predicting business failure [22].

More recently, researchers have begun to explore various models that combine different ML techniques or integrate ML with traditional statistical methods. These models have shown promising results in terms of prediction accuracy [18,19]. While financial ratios have traditionally been used as predictive variables, recent studies have begun to consider non-financial indicators, such as corporate governance factors, and macroeconomic variables [17]. In addition to general models, some studies have developed industry-specific prediction models, recognizing that the key predictors of business failure may vary across industries [5].

Long short-term memory (LSTM) networks are a type of recurrent neural networks (RNN) capable of learning long-term dependencies, making them well-suited for time-series data. They have been applied to many applications such as stock price forecasting and business failure prediction [14,24,27]. LSTM's effectiveness in business failure prediction lies in its ability to understand the temporal dynamics of financial data. Many scholars utilized LSTMs in predicting corporate financial distress and found them to perform well on longitudinal financial data. Compared to traditional statistical models and some AI models, LSTM has shown superior performance. For example, in [14], the authors used the LSTM RNN to predict the bankruptcy risk of construction contractors. Compared with the feedforward neural network and support vector machine models, the accuracy and F-1 score of the proposed LSTM RNN model were evaluated, and the optimal parameters were selected by five cross-validated grid searches. The results show that the prediction performance of the proposed LSTM RNN model is better than that of fuzzy neural networks and support vector machine models on both test data and original data sets.

Hybrid models combining LSTM with other techniques have been explored. For instance, a hybrid model that combines LSTM with a variational autoencoder (VAE) for bankruptcy prediction was proposed in [21]. The VAE is used to learn a low-dimensional representation of the financial ratios, which is then fed into the LSTM for prediction. The proposed model achieved higher accuracy than standalone LSTM and traditional models. Similarly, a study integrated LSTM with graph convolutional metworks to incorporate both temporal financial data and the company's position within a business network. Their proposed model significantly outperformed standalone LSTM and other benchmark models [27]. Those neural networks with autoencoder techniques have many practical applications [9, 21].

LSTM and its hybrid models have shown great potential in predicting business failures due to their ability to process sequential data and capture long-term dependencies. While the accuracy rates are generally superior to traditional and other AI models, the performance can variously depend on the specific dataset and implementation details.

More recent studies explore a BiLSTM network that is particularly suited for sequence prediction problems. The BiLSTM network trains two LSTMs on the input sequence: one on the original sequence and another on a reversed copy of the sequence. This approach enables the model to capture both past (backward) and future (forward) information. BiLSTM models have been utilized in various fields worldwide with proven results, such as text summarization in natural language processing, protein structure prediction, and daily stock prices prediction [1, 10, 13]. BiLSTM models offer a powerful tool for sequence prediction problems and have been used across various fields [25]. Their application in business failure prediction is still emerging. While significant advancements have been made in business failure prediction models, there remain challenges such as dealing with data imbalance and feature selection.

3. Method.

3.1. **Data preprocessing.** Based on existing research and current needs in the Australian construction industry, we select a number of insolvency indicators based on the following criteria: i) The chosen indicators have been studied in various research papers and their scientific and financial significance are widely recognized. ii) The indicators selected should be able to accurately reflect a construction company's overall situation. The indicators should cover not only the company's financial status, but also its operational status and the macroeconomy. iii) The selected indicators should be derived from the datasets obtained and, using relevant data, necessary ratios can be calculated.

In this study, we chose 17 financial ratios as decision variables. These variables have been divided into five indicator groups. The first group is the solvency indicator group, which demonstrates a company's ability to repay its debts. According to optimal capital structure theory, the weighted average capital cost of the capital raised by the enterprise through equity and debt financing is the lowest over a given time period, and the enterprise's market value is maximized. As a result, companies in construction must find a balance between equity and liabilities. If the debt ratio cannot be reasonably arranged, the company will be unable to repay its debts and may even go bankrupt. As a result, the solvency index is a critical factor in predicting a company's financial distress. In the first group, We used five insolvency indicators: the equity ratio, the debt-to asset ratio, the current ratio, and the working capital to total asset. The second group, referred to as the profitability indicator group, is made up of the return on sales, return on assets, return on equity, and net profit margin. This group measures the company's capacity to generate profits over a specific time period. The profitability and the company's capacity to withstand financial risks increase with the profit rate. The third group is the operating capability indicator group, which reflects the company's capacity to generate profits from a variety of its own assets. The asset turnover ratio, equity turnover ratio, total asset turnover, and the total liabilities to net worth are the four indicators we chose. These metrics reflect the company's capital operation turnover as well as how effectively it manages and utilizes its financial resources. Next, the growth capability group indicators indicate a company's potential ability to increase its operating scale and profitability in order to ensure its survival, and they make up the following group. An enterprise's growth capability index is primarily reflected in two areas. It reflects changes both in the company's existing assets, and in the profitability of the company. Finally, the macroeconomic environment indicator group reflects the economic circumstances of Australian economy and financial markets, using the gross domestic product, and the consumer price index, and unemployment rate. Table 1 shows the specific formulae to calculate these financial ratios.

We gathered a sample of data from several Australian construction company databases, including Australian Securities and Investment Commissions, Ibisworld, Company 360, Dun and Bradstreet. To investigate insolvency data, this research considered both publicly listed and privately owned Australian construction companies, being in operation for a minimum of six years prior to bankruptcy between 2000 and 2020. Finally, we acquired a total of three years of financial data from 29 solvent and 9 bankrupt firms. The data set included 111 insolvent observations and 27 insolvent observations. The ratio of insolvent observations to solvent observations was significantly higher. Then, following [14], this study employed SMOTE+Tomek links to address the imbalance classification problem, which combines the SMOTE capacity to produce synthetic data for the minority class and the Tomek links ability to remove the data that are classified as Tomek links from the majority class [7, 12]. We obtained 180 observations for the study after being processed using SMOTE + Tomek links, and the number of both insolvent observations and solvent observations was 90. Fig. 1 demonstrates the original data set and Fig. 2 shows the data set with SMOTE + Tomek links in three dimensions, where the X, Y, and Z axes stand for the most principle components after using principle components analysis.

Data normalization is the last stage of data preprocessing. Varied forms of data have different measurement ranges, and data with a broader range will cause a higher impact than those with a smaller range. In order to lessen the impact of the measurement range on the prediction model, we used equation (1) to normalize all

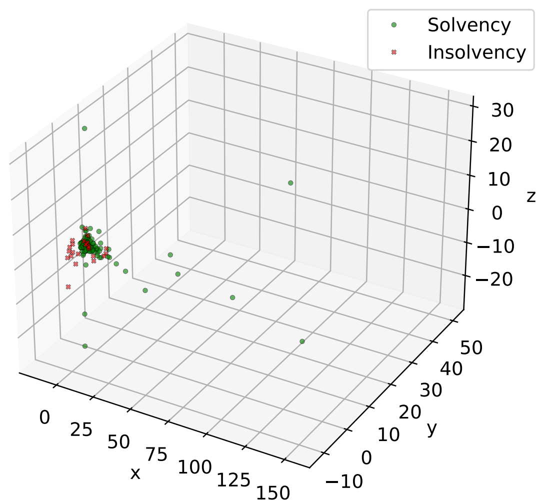

FIGURE 1. Orginal data set.

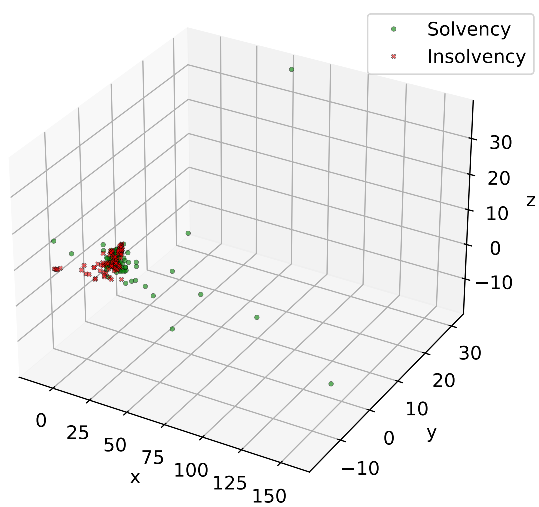

FIGURE 2. Data set with SMOTE + Tomek links.

data prior to learning and training, given by

$$x = \frac{x_{\text{original}} - x_{\text{mean}}}{\tau} \tag{1}$$

where x is the variable value with the value range $[0, 1]$, x_{original} is the original variable value, x_{mean} is the mean of the variable, and τ is the standard deviation the variable.

3.2. **Model construction.**

3.2.1. *LSTM and BiLSTM models.* LSTM is an improved recurrent neural network with feedback connections. In order to efficiently memorize and preserve sequential data features, LSTM introduces a gate structure that restricts the course of information transmission. The forget gate f_t, the input gate i_t, and the output gate o_t are the three gating structures that serve as the LSTM network's recurrent unit's major structural components. Specifically, in the forget stage, the forget gate f_t determines how much useless information of the preceding c_{t-1} must be forgotten. In the memory cell, the input i_t chooses and controls the data that needs to be saved for the candidate state at time step t. In the output stage, the output gate o_t chooses the information that the current state c_t is output to the external state h_t. The input, output, and forget gates, as well as one or more memory cells, are present in every memory block. The LSTM memory block with one memory cell is shown in Fig. 3. The associated cell state will be updated by

$$i_t = \sigma\left(W_i X_t + U_i h_{t-1} + b_i\right) \tag{2}$$

$$f_t = \sigma\left(W_f X_t + U_f h_{t-1} + b_f\right) \tag{3}$$

$$o_t = \sigma\left(W_o x_t + U_0 h_{t-1} + b_0\right) \tag{4}$$

$$\tilde{c}_t = \tanh\left(W_c x_t + U_c h_{t-1} + b_c\right) \tag{5}$$

$$c_t = f_t \otimes c_{t-1} + i_t \otimes \tilde{c}_t \tag{6}$$

$$h_t = o_t \otimes \tanh(c_t) \tag{7}$$

where x_t is the input at the t-th time; h_t is the hidden state at the t-th time; W_i, W_f, W_o, W_c, U_i, U_f, U_o, U_c are weight matrices; b_i, b_f, b_o, b_c are the bias vectors; σ is the sigmoid activation function; $\otimes$ is the element-wise product operation.

LSTM networks often employ one-way transmission of information, implying that they can only use information from the past and not from the future. BiLSTM networks take into account both historical and upcoming data. It is accomplished by coupling two LSTM networks with different timings using the same output. The forward LSTM can receive the input sequence's past data, while the reverse LSTM can obtain the input sequence's future data. BiLSTM's network architecture can be seen in Fig. 4 and its hidden state H_t at the t-th time comprises both the forward and reverse directions. The BiLSTM's hidden state can be described by

$$\overrightarrow{h_t} = \overrightarrow{\mathrm{LSTM}}\left(h_{t-1}, x_t, c_{t-1}\right) \tag{8}$$

$$\overleftarrow{h_t} = \overleftarrow{\mathrm{LSTM}}\left(h_{t+1}, x_t, c_{t+1}\right) \tag{9}$$

$$H_t = \left[\overrightarrow{h_t}, \overleftarrow{h_t}\right] \tag{10}$$

3.2.2. *Proposed BiLSTM autoencoder model.* We developed an insolvency prediction model integrating the BiLSTM network and the autoencoder framework, as shown in Fig. 5. A data collection of three years is used as input for the prediction model, where t is the year of forecasting insolvency. The neural network architecture of the BiLSTM autoencoder model for predicting bankruptcy employs BiLSTM layers to encode and decode the input data. These autoencoders can expand the relatively small dataset for predicting insolvency. Traditional linear and non-linear transformation and distortion methods cannot be employed for the transformation variant dataset, however autoencoders can be a suitable replacement [8]. Autoencoders attempt to replicate their input as their output. The encoder as well as the decoder are the standard components of an autoencoder's design (see the BiLSTM

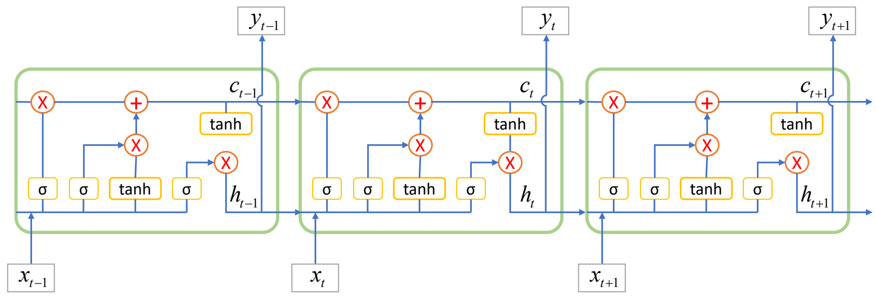

FIGURE 3. LSTM network architecture.

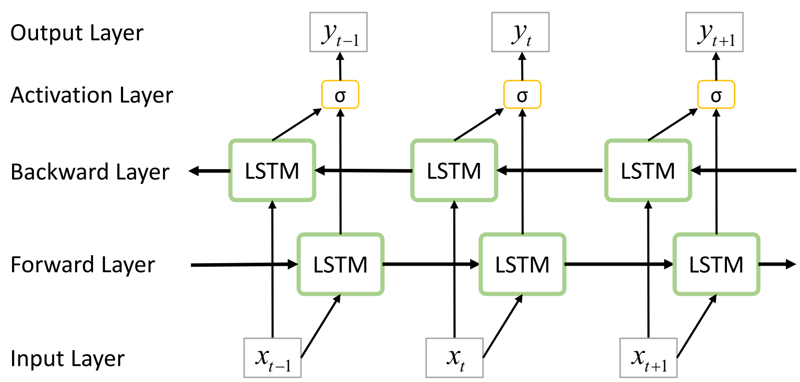

FIGURE 4. BiLSTM network architecture.

autoencoder layer in Fig. 5). A compressed version of the original input is generated by the encoder. Based on the correlations between input characteristics, the decoder decompresses the representation into a new input that has been rebuilt. The encoder uses BiLSTM layers to translate the input time series data to a lower-dimensional representation. A two-layer BiLSTM encoder is designed in this paper. While the first layer has 32 LSTM cells, the second layer has 16 LSTM cells. The feature vector of the input data that has been encoded is the second layer's output. The original financial data is reconstructed by the decoder using an additional set of BiLSTM layers, using the encoded representation as the starting point. In the opposite sequence as the encoder, the decoder layers are layered. This results in the first decoder layer having 16 LSTM cells and the second decoder layer having 32 LSTM cells. Reconstructing our model's input is the decoder's final output. The reconstruction error between the input data and the decoder's output is assessed in order to forecast insolvency. Therefore, we improve the accuracy of predictions by utilizing a BiLSTM autoencoder-based technique.

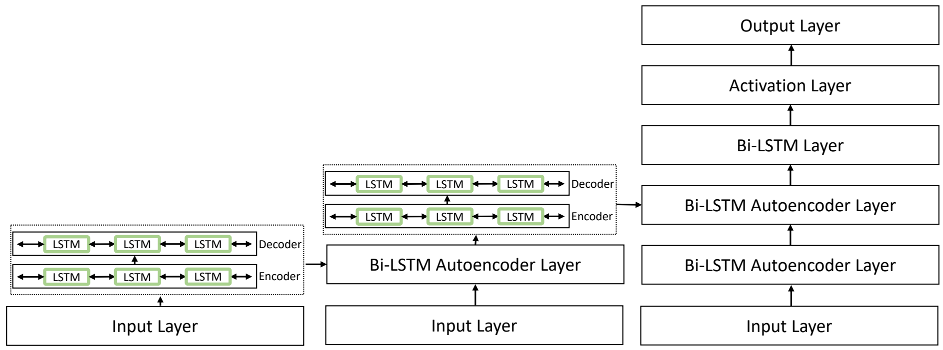

Figure 5. Proposed BiLSTM autoencoder network architecture.

4. **Experiment results.** As a benchmark for comparison, the proposed BiLSTM autoencoder model was employed to assess the performance of prediction models utilizing LSTM, BiLSTM, and CNN-BiLSTM. Four measures (accuracy, recall, precision, and F1-score) were utilized to assess the effectiveness of the categorization approaches. The percentage of correctly categorized data instances over all data instances is known as accuracy. The percentage of events that are accurately anticipated as positive is represented by recall. Precision measures how many of the points predicted as rare are actually rare, whereas recall measures how many of the rare points are predicted to be rare. It can estimate the probability that a positive prediction is correct. The F1-score is a metric which takes into account both precision and recall is also the harmonic mean of precision and recall. The four metrics can be obtained by the following equations:

$$\mathrm{Accuracy} = \frac{\mathrm{TN} + \mathrm{TP}}{\mathrm{TP} + \mathrm{FP} + \mathrm{TN} + \mathrm{FN}} \tag{11}$$

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{12}$$

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{13}$$

$$\text{F1-score} = \frac{2 * \mathrm{Precision} * \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{14}$$

where TP (True Positive) denotes the count of companies that were correctly predicted to be insolvent, TN (True Negative) denotes the count of companies that were correctly predicted to be solvent, FP (False Positive) denotes the count of companies that were correctly predicted to be solvent but were mistakenly diagnosed as insolvent, and FN (False Negative) denotes the count of insolvent companies that were incorrectly identified as solvent.

We have also determined the performance measures for our suggested model using equations (11) to (14). Additionally, we evaluated how effectively our model performed against LSTM and BiLSTM with identical parameters. Table 3 provides a summary of the results of the study, which demonstrates that utilizing the suggested BiLSTM autoencoder model significantly improves all performance measures.

5. **Conclusion.** This paper has developed a business insolvency prediction model for Australian construction companies using a deep learning model with BiLSTM autoencoder. Seventeen prediction indicators have been utilized to construct the proposed model that can forecast business insolvency based on a three year dataset. SMOTE-Tomek linkages were used to solve the imbalanced classification problem. This paper compared the accuracy, precision, recall, and F1-score values of the proposed model with those of other three prediction models. The empirical findings demonstrated that the proposed BiLSTM autoencoder network performed the best. The proposed model can potentially assist managers, investors, and government agencies in forecasting construction company insolvency, and it can also be tailored to prediction problems of other industry sectors.

TABLE 1. Insolvency prediction indicators

Level One Indicator	Level Two Indicator		Computation Description
Solvency Indicator	Equity Ratio	x_1	(Total Assets - Total Liabilities) /Total Assets
	Debt-to-Asset Ratio	x_2	Total Liabilities/Total Assets
	Current Ratio	x_3	Current Assets/Current Liabilities
	Working Capital to Total Asset	x_4	(Current Assets - Current Liabilities) /Total Assets
Profitability Indicator	Return on Sales	x_5	Net Profit/Net Sales
	Return on Assets	x_6	Total Profit/Total Assets
	Return on Equity	x_7	Net Profit/Shareholder's Equity
	Net Profit Margin	x_8	Net Profit/Revenue
Operating Capability Indicator	Asset Turnover Ratio	x_9	Net Sales/Average Total Assets
	Equity Turnover Ratio	x_{10}	Net Sales/Shareholder's Equity
	Total Asset Turnover	x_{11}	Net Sales/Total Assets
	Total Liabilities to Net Worth	x_{12}	Total Liabilities/Shareholder's Equity
Growth Capability Indicator	Net Profit Growth Rate	x_{13}	(Current Period Net Profit-Prior Period Net Profit)/Prior Period Net Profit
	Asset Growth Rate	x_{14}	(Current Period Assets -Prior Period Assets)/Prior Period Assets
Macroeconomic Environment Indicator	Gross Domestic Product	x_{15}	
	Consumer Price Index	x_{16}	
	Unemployment Rate	x_{17}	

Table 2. Statistics information of input indicators

Indicator	Max	Min	Mean	Std
Equity Ratio	3.33	-6.93	0.256	1.06
Debt-to-Asset Ratio	7.93	-2.33	0.744	1.06
Current Ratio	8	-0.78	1.8	1.3
Working Capital to Total Asset	3.15	-7.98	0.12	1.06
Return on Sales	1.41	-6.41	0.14	0.59
Return on Assets	2.46	-2.6	0.34	0.44
Return on Equity	1.5	-1.27	0.234	0.33
Net Profit Margin	1	-10.48	-0.045	0.93
Asset Turnover Ratio	9.97	0.04	2.36	1.67
Equity Turnover Ratio	158.5	-2.91	9.471	18.3
Total Asset Turnover	11.56	0.04	2.436	2.01
Total Liabilities to Net Worth	68.88	-3.35	3.087	7.85
Net Profit Growth Rate	31.43	-29.7	-0.132	4.41
Asset Growth Rate	3.27	-0.95	0.069	0.38
Gross Domestic Product	2.22	1.795	1.944	0.08
Consumer Price Index	128.7	114.2	121.2	2.98
Unemployment Rate	7.5	4.9	5.98	0.99

Table 3. Comparison of the prediction performance for LSTM, BiLSTM, CNN-BiLSTM and the proposed model

	Training data set			
Models	Accuracy	Precision	Recall	F1-score
LSTM	0.848	0.862	0.833	0.850
BiLSTM	0.898	0.853	0.967	0.906
CNN-BiLSTM	0.966	0.967	0.967	0.970
Proposed Model	**0.978**	**0.986**	**0.968**	**0.974**
	Test data set			
Models	Accuracy	Precision	Recall	F1-score
LSTM	0.733	0.800	0.571	0.670
BiLSTM	0.933	0.875	0.989	0.933
CNN-BiLSTM	0.933	0.875	**0.990**	0.930
Proposed Model	**0.973**	**0.990**	0.948	**0.969**

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