Predicting Vietnamese Stock Market Using the Variants of LSTM Architecture

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Abstract. Recently, the problem of stock market prediction has attracted a lot of attention. Many studies have been proposed to apply to the problem of stock market prediction. However, achieving good results in prediction is still a challenge in research and there are very few studies applied to Vietnamese stock market data. Therefore, it is necessary to improve or introduce new forms of prediction. Specifically, we have focused on the stock prediction problem for the Vietnamese market in the short and long term. Long short-term memory (LSTM) based on deep learning model has been applied to big data problem such as VN-INDEX. We compared the prediction results of the variants of the LSTM model with each other. The results obtained are very interesting that the Bidirectional LSTM architecture gives good results in short- and long-term prediction for the Vietnamese stock market. In conclusion, the LSTM architecture is very suitable for the stock prediction problem in the long- and short- term.

Keywords: LSTM · Bidirectional LSTM · VN-INDEX · Stock market prediction

1 Introduction

In fact, there is a lot of research related to stock predictions from many fields such as economics and computer science [1–3]. In computer science, scientists often use historical data such as opening prices, closing prices, highest price, lowest price, and trading volumes to predict the future prices of stocks [4]. There are many methods to forecast the stock market. Traditional methods are ARIMA (Autoregressive Integrated Moving Average) [5], ARMA (Autoregressive Moving Aver-age) [6], AR (Autoregressive) [7]. The advantage of these methods is that they are well suited to time series data such as stock markets. However, these methods give poorly results of prediction for big data and have not learned all the features of the data through the training process compared to modern methods such as deep learning [8].

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Recently, deep learning methods have been widely used for classification and prediction problems [9]. Because of its good computational infrastructure, this method is applied to many fields such as speech recognition, financial analysis, image processing, and natural language processing [10, 11]. The deep learning methods can train big data and learn data features, so this method gives good results. In fact, the data of the stock prediction problem is big data because it is collected from many transactions over ten years at stock exchanges. Recently, some studies have been applied to the stock market prediction problem [12–14]. However, these methods are often applied to data from international exchanges such as the SP&500, Nikkei, and Shanghai Index. There are very few applied studies on the VN-INDEX dataset of the Ho Chi Minh Stock Exchange. Besides, these studies only predict in the short-term period. Actually, studies with long-term predictions are not available.

For the researches in Vietnam in recent years, there are also some studies on the prediction problem for the stock exchange [15]. In particular, there are studies that use Internet news to make predictions related to the rise and fall of the stock market [16, 17]. In addition, there are studies that evaluate the role of investor behavior in the stock market based on the relationship between investor behavior and profits [18]. The common feature of recent studies is to focus on studying each news, political, and social relationship that affects stock market prices. In addition, there are a number of studies that apply deep learning techniques to predict stock prices [19, 20]. However, these studies have not focused on the problem of long-term prediction for the increase or decrease of stock prices.

Therefore, in this paper, we focus on researching using data of VN-INDEX of Ho Chi Minh City exchange over a long period of time. We choose the closing price to characterize the predictive analysis. With a large amount of data, we applied deep learning to two basic problems: short-term and long-term prediction. The very interesting results obtained are that the Bidirectional LSTM is well suited for short-term and long-term stock prediction.

The rest of this paper is organized as follows. Section 2 describes the methodology. Section 3 presents the experiments and their results. Finally, the main findings of this paper are concluded in Sect. 4.

2 Preparations and Methodology

2.1 Datasets

In this study, we used the VN-INDEX database on securities of Ho Chi Minh City exchange. Transactions are collected from the date 31st of July, 2000 to the date 25th of March, 2021. VN-INDEX stock data has been used in many recent studies [15, 21]. However, our study collected data for the most recent new transactions compared to other studies.

2.2 Introduction to Deep Recurrent Neural

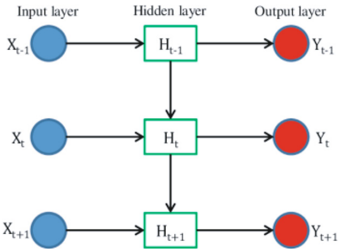

Fig. 1. A network architecture of deep recurrent neural

Deep learning is used to design computational layers that can learn from input data. Each layer in the architecture is designed to output informational features from the input. The first output of each layer is the beginning of the next layer. One of the techniques used for architecture of construction is RNN. This architecture uses input data to learn weights in the network. While the network is built from scratch with data, the special importance of the information will be stored in the hidden network states. Backpropagation is used to construct technical trainings for the network. calculations will be performed in sequence time and linked steps. Figure 1 shows the architectural benchmark of a deep RNN and the processes of prediction.

2.3 Definition of Long-Short Term Memory (LSTM)

The LSTM is proposed by Hochreiter and Schmidhuber [22], is one of the variants of RNN to solve the gradient loss problem. It can define ports, which can receive information by keeping vital information of the data. A learning process through backpropagation can estimate weights to allow data in cells to be saved or deleted. The formulas of the LSTM are as follows:

$$
\begin{aligned}
i_t &= \sigma(W_i x_t + U_i h_{t-1} + V_i c_{t-1}) \\
f_t &= \sigma\left(W_f x_t + U_f h_{t-1} + V_f c_{t-1}\right) \\
o_t &= \sigma(W_o x_t + U_o h_{t-1} + V_o c_t) \\
\tilde{c}_t &= tanh(W_c x_t + U_c h_{t-1}) \\
c_t &= \int_t^i \odot c_{t-1} + i_t \odot \tilde{c}_t \\
h_t &= o_t \odot + \tanh(c_t)
\end{aligned}
$$

where i_t indicates the input port and o_t indicates the output port. Where f, c_t, and h_t indicate forget gate, memory cell, and hidden state, respectively.

2.4 Definition of Bidirectional LSTM (BLSTM)

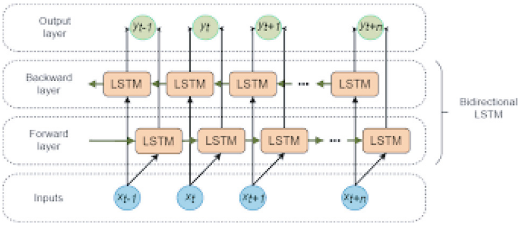

Fig. 2. Architecture of bidirectional RNN

One of the variants of RNN is Bidirectional RNN (BRNNs), this model was developed by Schuster and Paliwal [23]. BRNNs connects two hidden layers with opposite directions but same output. With This design, the output layer can get information from the backwards and from the forward states at the same time. BRNNs are proposed to enhance the processing of input data for the network. Figure 2 shows the effectiveness of BRNNs over unidirectional LSTMs in some application problems such as classification.

2.5 Formulation of Short-Term and Long-Term Prediction and Evaluation of Performance of Models

In this article, we use data of 15 days to predict the next day's price of a security and make a long-term prediction for the next 60 days. Besides, we used 3 error measures as follows:

$$MAE = \frac{1}{n} + \sum_{t=0}^{n-1} |y_t - \hat{y}_t| \tag{1}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=0}^{n-1} (y_t - \hat{y}_t)^2} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{t=0}^{n-1} (y_t - \hat{y}_t)^2}{\sum_{t=0}^{n-1} (y_t - \overline{y})^2} \tag{3}$$

Formula (1) is Mean Absolute Error (MAE), formula (2) is Root Mean Square Error (RMSE) and formula (3) is R^2. MAE and RMSE if close to zero is better for model prediction, otherwise R^2 is closer to 1 is better.

3 Results

We have conducted experiments using Python programming language and Keras open source library for deep learning with TensorFlow backend [24]. The closing price has been chosen as the only feature used to predict and evaluate the predictive capacity of the model. We have done the practice of dividing the data set into two parts. Part 1 takes up 80% of all data, and part 2 takes 20% for testing. We have also used this same data set for different algorithms LSTM, SLSTM and BLSTM. We have conducted using three error measures that are MAE, RMSE and R^2. Next, I experimented four times with different numbers of neurons increasing from 5, 10, 20, and 40 for both short-term and long-term prediction problems with all three models. The tables show the prediction results of the three models LSTM, SLSTM, and BLSTM, below.

Table 1. Short-term prediction results of LSTM model

Networks	MAE		RMSE		R square
	Testing	Training	Testing	Training	
5 neurons network	5.780	4.902	46.568	32.271	0.829
10 neurons network	4.316	3.660	26.53	20.473	0.944
20 neurons network	4.617	3.681	27.991	20.740	0.938
40 neurons network	4.38	3.594	26.000	20.333	0.946
Total average	4.773	3.959	31.772	23.454	0.914

Table 2. Short-term prediction results of SLSTM model

Networks	MAE		RMSE		R square
	Testing	Training	Testing	Training	
5 neurons network	5.730	4.872	46.287	31.963	0.833
10 neurons network	5.097	4.277	36.396	26.468	0.897
20 neurons network	5.321	4.0481	36.170	24.926	0.898
40 neurons network	4.735	3.898	30.260	23.201	0.929
Total average	5.220	4.273	37.278	26.639	0.8892

Table 3. Short-term prediction results of BLSTM model

Networks	MAE		RMSE		R square
	Testing	Training	Testing	Training	
5 neurons network	4.821	3.893	30.435	21.767	0.928
10 neurons network	4.071	3.334	23.383	17.488	0.957
20 neurons network	4.236	3.535	25.400	19.826	0.949
40 neurons network	4.180	3.532	16.848	19.683	0.977
Total average	4.327	3.573	24.016	19.691	0.952

Table 4. Long-term prediction results of LSTM model

Networks	MAE		RMSE		R square
	Testing	Training	Testing	Training	
5 neurons network	5.578	6.632	40.114	67.295	0.874
10 neurons network	4.755	6.951	28.202	70.524	0.938
20 neurons network	8.283	6.726	74.861	70.267	0.564
40 neurons network	7.009	6.886	56.665	67.661	0.750
Total average	6.406	6.798	49.96	68.936	0.781

Table 5. Long-term prediction results of SLSTM model

Networks	MAE		RMSE		R square
	Testing	Training	Testing	Training	
5 neurons network	6.543	6.955	57.997	75.069	0.738
10 neurons network	7.008	6.915	61.34	74.578	0.707
20 neurons network	6.828	6.89	58.506	74.408	0.733
40 neurons network	5.329	7.492	38.45	78.215	0.885
Total average	6.427	7.063	54.073	75.567	0.765

Table 6. Long-term prediction results of BLSTM model

Networks	MAE		RMSE		R square
	Testing	Training	Testing	Training	
5 neurons network	4.981	7.027	33.635	70.004	0.912
10 neurons network	4.757	7.164	29.799	72.274	0.930
20 neurons network	4.513	6.992	27.566	70.141	0.940
40 neurons network	6.363	6.582	47.806	67.360	0.822
Total average	5.153	6.941	34.701	69.944	0.901

Based on the experimental results, we have given in the above six tables the results. We can comment as follows: Tables 1, 2, and 3 show the results for the short-term prediction of three models: LSTM, SLSTM, and BLSTM. Tables 4, 5, and 6 are the results of long-term stock price predictions. For short-term prediction, the average result of LSTM on the test data set with error measures MAE, RMSE, and R^2 is 4,773, 31,772, and 0.914, respectively, and the average result of SLTSM on the test data set with error measures MAE, RMSE and R2 are 5,220, 37,278, and 0.8892, respectively, the average result of BLSTM is 4.237, 24,016 and 0.952, respectively. Based on this result, we can see that the BLSTM model gives better results than the LSTM and SLSTM models when it comes to short-term prediction. Similarly, we evaluate the results when predicting long-term with three models LSTM, SLSTM, and BLSTM. The average result of the LSTM with the three error measures MAE, RMSE, and R^2 is 6,406, 49,960, and 0.781, respectively, and the mean result of the SLSTM with MAE, RMSE, and R^2 is 6,427, 54,073, and 0.765, respectively. The results of the BLSTM model with three error measures MAE, RMSE, and R^2 are 5.153, 34,701, and 0.901, respectively. Based on this result, we can say that the BLSTM model gives the best results on the test set with error measures MAE, RMSE, and R^2 for both short-term and long-term prediction problems for the VN-INDEX.

We conduct one more experiment, we proceed to select the best model of LSTM, SLSTM, and BLSTM. The results for the short-term prediction problem are shown in Table 7 below. Based on the results of Table 7, we can see that the BLSTM model gives good predictive results on both the training and testing datasets. Similarly, the best models for long-term prediction are shown in Table 8. The results show that the BLSTM model gives the best prediction results for the long-term prediction problem on the testing dataset. In addition, we simulated the results of the models in Figs. 3 and 4.

Table 7. Results of comparing the best models for short-term prediction problem

	Training			Testing		
	MAE	RMSE	R^2	MAE	RMSE	R^2
LSTM	3.594	20.333	0.946	4.380	26.000	0.946
SLSTM	3.898	23.201	0.929	4.735	30.260	0.929
BLSTM	3.532	19.683	0.977	4.180	16.848	0.977

Table 8. Long-term prediction results of the best models

	Training			Testing		
	MAE	RMSE	R^2	MAE	RMSE	R^2
LSTM	6.886	67.661	0.75	7.009	56.665	0.75
SLSTM	7.492	78.215	0.885	5.329	38.45	0.885
BLSTM	6.992	70.141	0.94	4.513	27.566	0.94

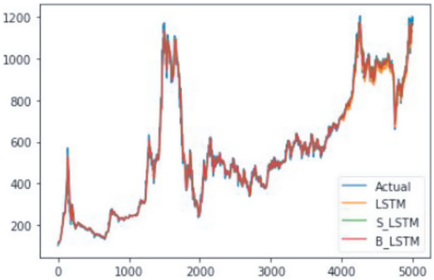

Fig. 3. Short-term prediction results using LSTM, SLSTM, and BLSTM

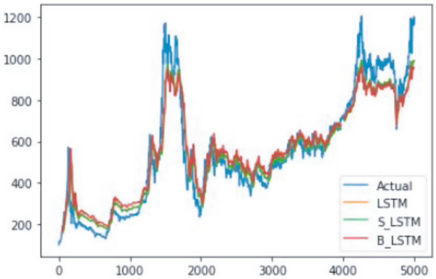

Fig. 4. Long-term prediction results of LSTM, SLSTM, and BLSTM models

4 Conclusion

In this paper, we have built a stock prediction problem. The selected data is VN-INDEX collected from the Ho Chi Minh City exchange from 31st of July, 2000 to 25th of March 2021. We have performed predictions for two problems which are short-term and long-term prediction problems. Three prediction models have been selected, namely LSTM, SLSTM, and BLSTM. The results show that the BLSTM model performed better than other models for this time -series data problem. In other words, the BLSTM model could be a favorable method to choose for predicting the Vietnamese stock market both in short and long-term periods.

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