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Deep Learning Approach in Predicting Property and Real Estate Indices

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Abstract

The real estate market is one of the most impacted sectors from the Corona Virus Disease 2019 (COVID-19) pandemic that happened in early 2020 globally. Here, we tried to apply an extension of the Long Short-Term Memory (LSTM) deep learning method, known as the Bidirectional LSTM (Bi-LSTM) networks for stock price prediction. Our focus is on six stocks that were included in the LiQuid45 (LQ45) property and real estate sectors. A simple three-layers Bi-LSTM network is proposed for predicting the stocks' closing prices. We found that the prediction results fall in the reasonable prediction category, except for Pembangunan Perumahan Tbk (PTPP). Bumi Serpong Damai Tbk (BSDE) got the highest accuracy result with more than 90% score, while PTPP got the lowest score with less than 8% score. The proposed Bi-LSTM network could provide a baseline result for developing a good trading strategy.

Keywords: *Bi-LSTM networks, deep learning, LQ45, property and real estate, stock price prediction.*

1 Introduction

The stock market is undoubtedly one of the world's most complex financial markets. Its basic instrument is the stock itself that can be easily exchanged and become the proof of ownership [1]. In the stock market, millions of transactions occurred daily in a very dynamic environment [2]. Its nature is nonlinear, highly unpredictable [3], [4] and therefore the future stock price prediction has become a very challenging task that attracts many researchers.

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In developing a good trading strategy, many researchers have predicted the stock's price movement by using various prediction methods. Many of them used fundamental and conventional technical methods, such as Moving Averages [5], [6] and AutoRegressive Integrated Moving Average (ARIMA) [7], [8], but the accuracy results are not good enough [3]. Therefore, other researchers tried to use more advanced techniques, such as soft computing and Machine Learning (ML), to solve the problem [1], [9]. Especially, in the last decade, a new domain in the Machine Learning area, known as Deep Learning, has emerged and gained wide popularity in various fields.

Deep Learning (DL) has gained its name from the deep network layers usage in its architecture. It has rapidly developed into many kinds of algorithms and techniques. In time series domain, the Long Short-Term Memory (LSTM) networks has been popularly used as a Deep Learning approach. It was developed from a special Neural Networks architecture, called the Recurrent Neural Network (RNN), and has been implemented for stock price prediction as can be found in [10]–[13]. Moreover, LSTM was further developed into many derived versions, one of them is the Bidirectional LSTM (Bi-LSTM), which has been widely used in classification problems, such as in the Natural Language Processing domain for text classification [14], in the medical domain for breast cancer detection [15], and in multimodal sensor domain for human activity recognition and fall detection [16].

Our aim in this study is to implement the Bi-LSTM approach in the regression task domain, especially for predicting the future stock prices based on available historical data in the stock market. We limit our focus to six stocks that are included in the property and real estate sectors of LiQuid45 (LQ45) indices. LQ45 indices listed 45 companies' stocks in Indonesia that have high liquidity and huge market share with a good financial status [9]. The list is assessed and reported by the Indonesia Stock Exchange (IDX) semi-annually [17] and can be accessed freely by the public via its legal website. Many stakeholders, including investors, traders, and researchers, used this list as one of their criteria in developing a good trading strategy [17]–[19]. Moreover, the property and real estate indices have become our interest due to the great COVID-19 pandemic effect on those indices. COVID-19 outbreak, which globally happened in early 2020, has severely impacted real estate markets [20]. Several studies have confirmed that housing prices have declined in several regions that are highly impacted by the COVID-19 pandemic [21]–[23].

In the following section, some related works will be described. Then, the research method conducted namely, the Bi-LSTM networks and some performance evaluation metrics, will be explained. Next, a more detailed description of the datasets used, the study results, and discussion will be given. Finally, some concluding remarks and suggestions for future research will be pointed out.

2 Related Work

Recent development of Machine Learning techniques, especially Deep Learning, have attracted many researchers to apply them in various scenarios. Particularly, in stock price prediction, Deep Learning techniques, such as Gated Recurrent Unit (GRU) and Long Short-Term Memory (LSTM), have gained increasing attention. Shah et al. [24], for example, they tried to implement Bidirectional LSTM (Bi-LSTM) in predicting two companies' stock prices, namely Tesla and Citi Bank. They used six years historical data of both companies and compared the results with the conventional LSTM method. They found the Bi-LSTM performed better than LSTM.

In a more advanced study, Yadav et al. [25] have introduced a hybrid Deep Learning model based on Fast Recurrent Neural Networks (FastRNN), Convolutional Neural Networks (CNN), and Bi-LSTM. They used 1 minute time interval data of four companies in one day period. The Root Mean Square Error (RMSE) and time computation are used to evaluate the model's performance. They found the proposed model outperformed other techniques, such as ARIMA and FBProphet.

On another work, Hansun and Young [26] have recently published a paper that aims to predict the financial sector indices of the most liquid companies in Indonesia. They implement the LSTM networks on six stocks and found that the proposed LSTM networks give promising results. One of the most important findings from the study is that even by using simple networks architecture, we could get good prediction results, especially for the regression task in Machine Learning domain.

3 Research Methods

Figure 1 shows the research flow for this research. We began the whole process by cleaning and processing missing values with a data imputation technique. Next, the cleaned data was split into training (80%) and test sets (20%). To get normalized training and test sets, a feature scaling technique was applied. Then, we reshaped training and test sets into 3-dimension arrays so it can be further processed in the proposed Bi-LSTM networks. A relatively simple Deep Learning (DL) architecture, which consists of a Bi-LSTM layer, followed by a Dropout layer, and ended by a Dense layer was introduced to solve the prediction problem. To get the prediction results and the performance evaluation of Bi-LSTM networks, we used the Mean Absolute Percentage Error and the Root Mean Square Error criteria.

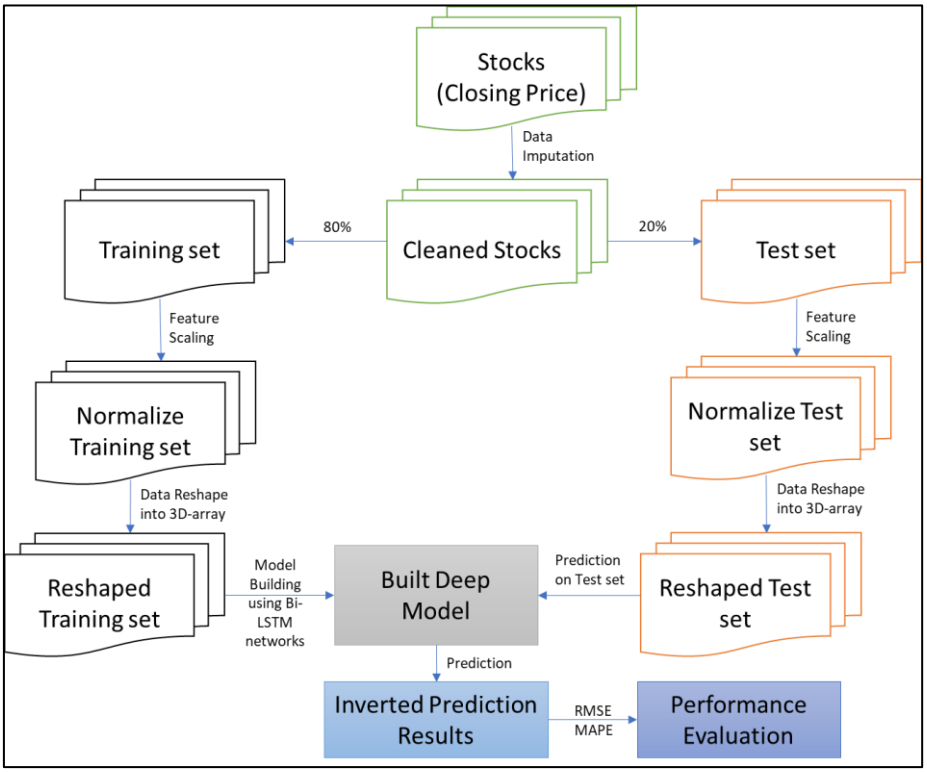


Fig. 1. Research Workflow

4 Bi-LSTM and Performance Metrics

Bi-LSTM is actually an extension of LSTM networks that employs the bidirectional structure of Recurrent Neural Networks (RNN) as proposed by Schuster and Paliwal [27]. The bidirectional structure can be applied to any RNN architecture, but it gained its most popularity as Bi-LSTM networks. In Bi-LSTM, there are two distinct LSTM hidden layers with similar output in opposite directions, i.e., the forward and backward directions [28]. In the forward direction, the network learned from increasing order of input sequence $\{x_1, x_2, \dots, x_n\}$, while in the backward direction it learned from decreasing order of input sequence $\{x_n, x_{n-1}, \dots, x_1\}$. After learning from the forward and backward LSTMs separately, their outputs are combined into one using any integration operators, such as concatenation, addition, etc. [29]. Using this approach, not only the information from the past can be preserved, but also the information from the future in the dataset [30]. Figure 2 depicts the comparison of typical LSTM and Bi-LSTM architectures [30].

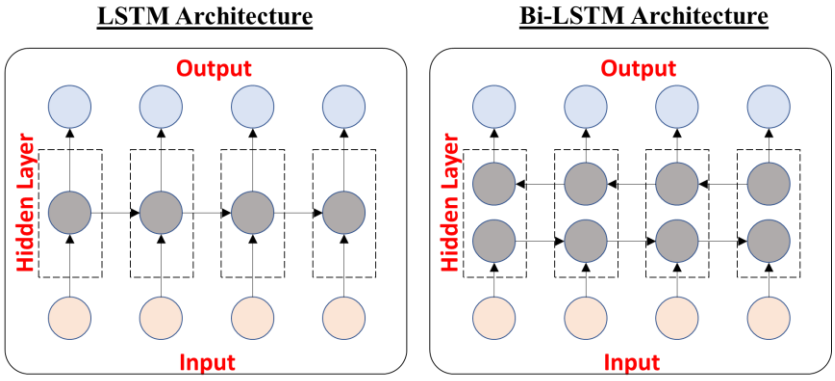


Fig. 2. LSTM vs Bi-LSTM Architectures

In this study, we used two error criteria, namely Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) criteria. As described by Rustam et al. [31] and Hansun et al. [32], those criteria can be expressed as Equations 1 and 2 below.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - F_t)^2} \tag{1}$$

$$MAPE = \left(\frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - F_t}{Y_t}\right|\right) \cdot 100\% \tag{2}$$

n is the total number of data, Y_t is the actual value, and F_t is the forecasted value. Moreover, we also calculated the R-squared (R^2) score, which is commonly used as the accuracy score for regression problems in the Machine Learning domain. Its values ranged from 0% to 100%, where 0% implies that the response variable has no variability around its mean explained by the learned model and 100% implies the response variable has the variability around its mean [31]. The R-squared score can be represented as Equation 3 below [33].

$$R^2 = 1 - \frac{\sum_{t=1}^{n}(Y_t - F_t)^2}{\sum_{t=1}^{n}(F_t)^2} \tag{3}$$

5 Results, Analysis and Discussions

As explained in the Introduction section, we limit our focus to several stocks that are included in the property and real estate sector in LQ45 indices. There are six considered stocks as shown in Table 1 that are listed in the last (Major Evaluation) Report in February to July 2021 period [34].

Table 1: LQ45 property and real estate sector stocks

Code	Stock Name
BSDE	PT Bumi Serpong Damai Tbk.
CTRA	PT Ciputra Development Tbk.
PTPP	PT PP (Persero) Tbk.

PWON	PT Pakuwon Jati Tbk.
SMRA	PT Summarecon Agung Tbk.
WIKA	PT Wijaya Karya (Persero) Tbk.

We downloaded the daily stock prices from Yahoo! Finance [35]. We used the maximum data available from the source up to May 1st, 2021. Next, the collected data were pre-processed to replace any missing values with their last known records. In the training and test sets splitting data, we used an 80:20 ratio. Table 2 shows the training and test sets of the considered stocks in this study.

Table 2: LQ45 property and real estate indices – train and test sets

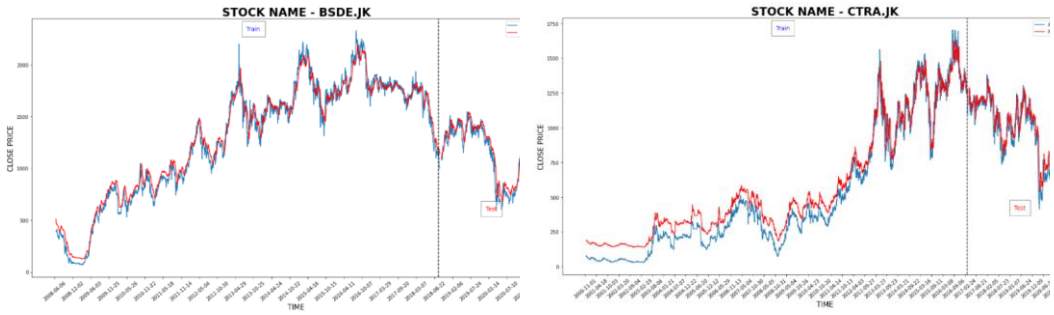
Code	Training	Test	Total	Missing Values
BSDE	2,556	640	3,196	1[a]
CTRA	4,110	1,028	5,138	2[b]
PTPP	2,230	558	2,788	1[a]
PWON	3,093	774	3,867	1[a]
SMRA	3,739	935	4,674	2[b]
WIKA	2,671	668	3,339	1[a]

[a] Missing value was found on 2019-06-19

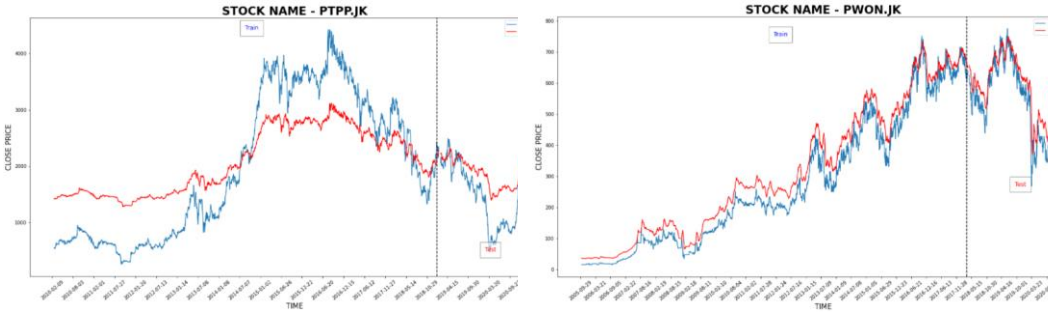
[b] Missing values were found on 2008-10-13 and 2019-06-19

In the next phase, we normalized the training and test sets by using a feature scaling technique and reshaped the datasets into a 3D-array so that they can be further processed by the Bi-LSTM networks in Keras. We proposed simple three-layers Bi-LSTM networks which consists of a Bi-LSTM layer, a Dropout layer, and a Dense layer. 200 hidden neurons were used in the Bi-LSTM layer and 20% dropped information was used in the Dropout layer to prevent overfitting. In compiling the network, we used the Mean Square Error (MSE) criterion with Adam optimizer. The model was trained for 20 training epochs with a batch size of 32. The built model will be used on the test set for predicting the future closing values of the considered stock.

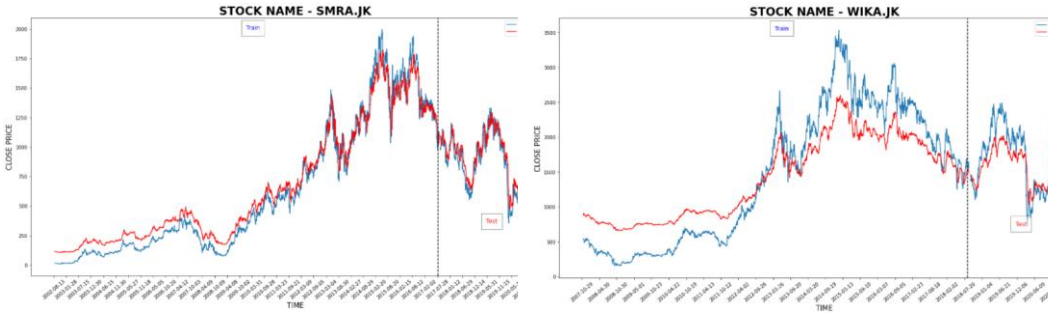
The prediction results for all six stocks included in the LQ45 property and real estate indices are plotted in Figure 3. As can be seen from the figure, the proposed Bi-LSTM architecture could give good prediction results.



(a) BSDE (b) CTRA



(c) PTPP (d) PWON



(e) SMRA (f) WIKA

Fig. 3. LQ45 Property and Real Estate Indices' Prediction Results

To know the performance of the learnt model on the test set, we evaluated the prediction results by using RMSE and MAPE criteria. Table 3 shows the RMSE and MAPE for each stock on the test set. As can be inferred from Table 3, the RMSE values are ranged from 52.4310 (PWON) to 485.8175 (PTPP), which depend on the magnitude of the stock's closing prices. Almost all of those six stocks have MAPE values under 50% that included as reasonable prediction results [36], except for PTPP (~54%). Therefore, the prediction results of LQ45 property and real estate indices using the Bi-LSTM network produced reasonable results that can help decision-makers, including investors, to make a good trading strategy in the future.

Table 3: RMSE and MAPE values

Code	RMSE	MAPE
BSDE	78.4851	28.6511
CTRA	83.6411	24.2246
PTPP	485.8175	53.9563
PWON	52.4310	23.7906
SMRA	86.4230	30.7648
WIKA	254.4500	26.8808

As for the prediction accuracy, we also calculated the R^2 score for each considered stock. Table 4 shows the R^2 score of the prediction results on the test set of each considered stock. Among those six stocks, BSDE has the highest accuracy with more than 90% score, while PTPP has the lowest score with around 8% score. The average accuracy value for all those stocks is around 68%, which is mainly caused by the very low accuracy score of PTPP. Therefore, except for PTPP, the built model using Deep Bi-LSTM networks could perform pretty well in predicting the future value of each considered stock. Another model-building strategy and parameter tuning should be performed for PTPP.

Table 4: Resulting R^2 scores

Code	R^2	**Code**	R^2
BSDE	90.8684	PWON	76.1066
CTRA	82.0458	SMRA	83.8115
PTPP	7.8312	WIKA	65.7692

6 Conclusion

Since the COVID-19 outbreak in late 2019, which then was announced as a global pandemic in early 2020 by the World Health Organization (WHO), it has affected almost all aspects of our lives. One of the most impacted sectors is the property and real estate markets around the world. In this study, we tried to predict six property and real estate indices included in LQ45. i.e., BSDE, CTRA, PTPP, PWON, SMRA, and WIKA. By using simple three-layers Bi-LSTM networks, we found that the built model could give good prediction results in almost all experimented stocks, except on PTPP. Therefore, another deep learning algorithm and model development strategy could be performed in the near future for PTPP. One possible approach to be used is the newer method in RNN family, i.e., the Gated Recurrent Unit (GRU).

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