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PREDICTING BANKING STOCK PRICES USING RNN, LSTM, AND GRU APPROACH

Abstract

In recent years, the implementation of machine learning applications started to apply in other possible fields, such as economics, especially investment. But, many methods and modeling are used without knowing the most suitable one for predicting particular data. This study aims to find the most suitable model for predicting stock prices using statistical learning with Arima Box-Jenkins, RNN, LSTM, and GRU deep learning methods using stock price data for 4 (four) major banks in Indonesia, namely BRI, BNI, BCA, and Mandiri, from 2013 to 2022. The result showed that the ARIMA Box-Jenkins modeling is unsuitable for predicting BRI, BNI, BCA, and Bank Mandiri stock prices. In comparison, GRU presented the best performance in the case of predicting the stock prices of BRI, BNI, BCA, and Bank Mandiri. The limitation of this research was data type was only time series data. It limits our instrument to four statistical methode only.

1. INTRODUCTION

Economic growth is one of the benchmarks and indicators of a country's development. Various factors can affect economic growth, including financial system stability. A stable financial system can maintain or improve the domestic economy in terms of capital flows. The role of financial system stability in Indonesia belongs to the banking sector. Bank Indonesia carries out several policies to maintain the stability of the bank-based financial system (Bank Indonesia, 2022).

In 2019, the world was shocked by the Covid-19 Pandemic, which originated in Wuhan, China. Covid-19 infection was first encountered in Indonesia in early 2020. The rapid spread and transmission of Covid-19 rushed the government to implement various policies, including social distancing, limited mobility, and gatherings (Wibowo, 2020). Such government policies also impacted various fields, including the economy, as seen from the decline in economic activity, bank performance, and increased inflation. On the other hand, rising inflation has pushed the central bank to raise interest rates, affecting bank liquidity, risk and profits (Ghenimi et al., 2021). Due to these circumstances, predicting banking stock prices has become a thought-provoking topic.

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A stock market is where companies issue their shares to expand their business, and investors can buy or sell each other's shares at certain prices. Investors around the world can buy and sell stocks, thus making a profit by selling at a higher price than they bought (Acheampong et al., 2014). The challenge is fluctuating stock price movements can change within minutes or seconds (Madge & Bhatt, 2015). Therefore, the theory of predicting stock prices emerges.

Stock market forecasting concerns accurately predicting stock prices to earn higher profits through trading (Acheampong et al., 2014). However, getting accurate predictions from stock trends is challenging due to nonlinear and fluctuating data conditions. Traditionally, some who believe in the efficient market hypothesis argue that future stock prices can be predicted based on historical stock data (Shahi et al., 2020). Generally, time series data is modeled using the Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) statistical model (Shumway & Stoffer, 2019). The ARIMA Box-Jenkins modeling assumes white noise in its parameter estimation. This is one of the weaknesses of ARIMA Box-Jenkins when applied to complex data.

Along the way, experts have found a machine learning-based data modeling method that is more flexible; it does not require certain assumptions and does not have specific parameters (Linardatos et al., 2021). Machine Learning applies a concept that forms an artificial neural network that works like a neural network in the human body. An artificial neural network, often called Multi-Layer Perceptron (MLP), is a system built from several nodes known as neurons (Taud & Mas, 2018). Although traditional MLP models, such as back-propagation, can identify nonlinear relationships between variables, they cannot reflect time series relationships between variables (Yang & Guo, 2021). Meanwhile, the temporal relationship between variables and the logical relationship behind them is very important.

Deep learning theory has developed rapidly in recent years with a rich set of tools widely used in signaling, image processing, data mining, etc. In addition, the deep learning model has excellent time series data processing capabilities, which achieves good economic and financial forecasting results (Najafabadi et al., 2015). This neural network component consists of at least an input, hidden, and output layer. Artificial neural networks have several methods of use, such as Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU), which are a form of Artificial Neural Networks (ANN) architecture and are specifically designed to process data that is continuous or sequential (sequential data). In this case, the three models are suitable for use in time series data.

2. LITERATURE REVIEW

Several previous studies have researched machine learning applications in the economic field, namely the use of LSTM to predict Indian Stock Market Prices which provides information that the LSTM model is preferred due to higher stability (Yadav et al., 2019, 2020). Other research related to LSTM in predicting stock prices (Ding & Qin, 2020; Moghar & Hamiche, 2020). RNN modeling to predict stock prices has been carried out by Jahan & Sajal (2018) in predicting Advanced Micro Device (AMD) stock prices. Jarrah & Salim (2019) stated that the RNN model is better than ARIMA in predicting Saudi Stock price trends. GRU modeling has been done by Gupta et al. (2022) in predicting the Indian stock market (CNX-Nifty).

This study aims to compare the performance of several time series data models with non-stationary properties using Jenkins' ARIMA Box as a statistical learning with RNN, LSTM, and GRU deep learning methods. RNN, LSTM, and GRU are three types of deep learning models specifically designed to process data that has a sequence or series, such as time data. Therefore, choosing RNN, LSTM, and GRU to compare is the right step in choosing the best model for a particular time series data. By comparing the three models, we can find out the advantages and disadvantages of each model in processing time series data, and find the best model for a specific case. Sezer et al (2020) conducted research on deep learning models, the results of their research stated that RNN, LSTM and GRU are the most common. To achieve this goal, the learning architecture is designed cooperatively, which can treat RNN, LSTM, and GRU models equally with the same input. This study uses stock price data for 4 (four) major banks in Indonesia, namely BRI, BNI, BCA, and Mandiri, from 2013 to 2022.

3. METHODE, DATA, AND ANALYSIS

3.1. ARIMA Box-Jenkins

Shumway & Stoffer (2019) mention that time series data $\{Yt\}$ is a series of random and correlated observations arranged according to time $t = \pm 1, \pm 2, \ldots, \pm n$. In statistics, time series data is a series of observational values that depend on current and past events measured over a certain period based on time with the same interval (W. W. S. Wei, 2006).

ARIMA Box-Jenkins can be interpreted as a combination of two models: the integrated Autoregressive (AR) and Moving Average (MA). This model uses information in the same sequence to form a model for forecasting (Shumway & Stoffer, 2019). In general, the ARIMA Box-Jenkins (p,d,q) model is as follows (Wei, 2006):

$$\phi_p(B)(1 - B)^d Y_t = \theta_q(B) a_t \tag{1}$$

where: p – orde from AR,
q – orde from MA,
d – orde from differencing,
$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$,
$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$,
$(1 - B)Y_t = Y_t - Y_{t-1}$,
Y_t – time series data.

a_t is a white noise sequence with zero mean and constant variance, while B is a backshift operator. Several methods can be used as estimate parameters, one of which is the Maximum Likelihood Estimation (MLE) method. The principle of the MLE method in estimating parameters is to choose a parameter value estimator that maximizes the probability of the observed (Shumway & Stoffer, 2019). After parameter estimation, a diagnostic test of the model is carried out with the assumption that the residual is white noise $(a_t \sim \mathrm{NIID}(0, \sigma_a^2))$.

3.2. RNN

RNN is one of the components of an artificial neural network with feedback connections closed by loop (Ahmad et al., 2022). RNNs are called "repetitive" because they perform the same task for each sequence element by leveraging previously captured information sequentially to predict future unknown sequential data (Ludwig, 2019). RNN is a regular back-propagation algorithm applied to non-repeatable networks taking weight sharing into account (Almalaq & Edwards, 2017). However, RNNs generally suffer from the loss of gradient values due to difficulty learning long-term dependencies (Bhatt et al., 2020). The RNN architecture is fully and partially interconnected, as shown in Figure 1.

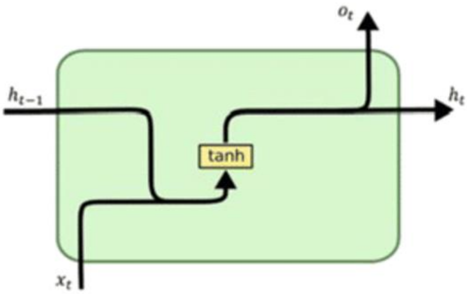

Fig. 1. RNN Architecture (Tembhurne & Diwan, 2021)

In a fully interconnected architecture, a fully connected network has no distinct neurons and each neuron has input from all other neurons. A partially connected RNN architecture is used for character string learning even though some neurons are part of the feedforward structure. There are three types of weights used in the RNN architecture. The weights in the RNN are the weights from the input layer to the hidden layer, the weights from the hidden layer to the output layer, and the weights from the context layer to the hidden layer (Zainab et al., 2019).

The weight estimation of the RNN model is carried out using the Gradient Descent method with momentum and adaptive learning rates used to increase the learning speed and maintain learning stability (Utomo, 2017). The ultimate goal of the Gradient Descent method with momentum and the adaptive learning rate is to minimize the residual until the value is less than the residual determined as the minimum limit. RNN learning can be done by updating the relationship weights based on the rules for updating the weights. The equation used to fix the weights in the RNN is in the following equation.

$$\Delta w_{ij}^{(k)} = w_{0j}^{(k)} + \Delta \mathrm{w}_{0\mathrm{j}}^{(\mathrm{k})} \tag{2}$$

$$= \Delta \mathrm{w}_{0\mathrm{j}}^{(k)} + m_{0j(k-1)}^{(k)} + \eta m_0 \frac{c_j}{N} \sum_{t=1}^{N} (\tilde{x} - x_i) f'(net_j) \tag{3}$$

Weight correction is carried out until the residual reaches the set value or the number of iterations has reached the specified maximum limit. One of the drawbacks is that the RNN network only store some of the data steps in the previous sequence. Thus, RNNs are not suitable for storing longer sequences. Another type of recurrent network, LSTM, was introduced to overcome this shortcoming.

3.3. LSTM

LSTM is a type of RNN that can store more memory sequences of data (Ludwig, 2019). Specifically, each LSTM contains a set of cells (modules) capturing and storing data streams. Cells that resemble transport links can connect one module with other modules conveying data from the past and collecting them for the present. A different gate in each cell allows data to be removed, filtered, or added to that cell. Thus, the gate allows the cell to let data pass through or be discarded optionally. The architecture of the LSTM is shown in Figure 2. The three types of gates involved in each LSTM cell are which are: Forget Gate: It displays the number [0,1] where 1 implies the flow and 0 implies block of data flow; Input Gate: It selects which data the cell needs to store; Output Gate: Output value is based on cell state, filtered data, and recently added data (Tsai et al., 2018).

LSTM superiorities include the constant backpropagation of errors in memory cells resulting in the ability of LSTM to bridge long-time lags. LSTM can handle noise, distributed representation, and continuity (Yang & Guo, 2021). Shumway & Stoffer (2019) said that time series data $\{Yt\}$ is a series of random and correlated observations arranged according to the time $t = \pm 1, \pm 2, \ldots, \pm n$. In statistics, time series data is a series of observational values that depend on current and past events measured over a certain period based on time with the same interval (Wei, 2006).

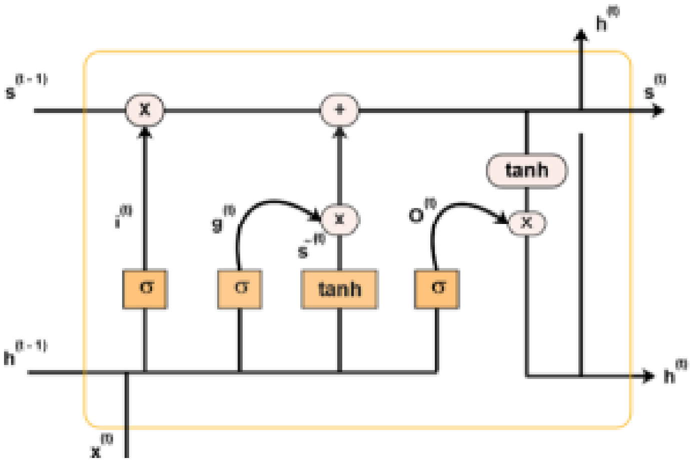

Fig. 2. LSTM Architecture (Khan et al., 2021)

3.4. GRU

GRU is a type of deep learning that can be used in data series as an alternative solution to reduce the complexity of LSTM units. GRU has fewer trainable parameters because it does not have the output layer like LSTM. Within GRU, the information flow control component is called a gate, and GRU has two gates, namely a Reset Gate and an Update Gate (Yang & Guo, 2021). The Reset Gate determines how to combine the new input with past information. Meanwhile, the Update Gate determines how much past information should be stored while reading the sequence. The GRU architecture is shown in Figure 3.

Although LSTM and GRU are very similar, they have some key differences. GRU has two gates (Reset and Update), while LSTM has three gates (Input, Output, and Forget). Reset Gate in GRU handles how new inputs are combined with previous memory, and Update Gate handles how much of the previous state needs to be maintained. Update Gate has the same job as Input and Forget Gates in LSTM. GRU has fewer parameters and complexity than LSTM.

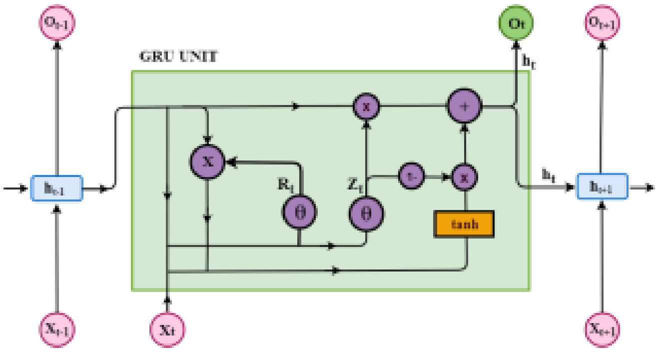

Fig. 3. GRU Architecture (Bibi et al., 2020)

The data used is stock data of the four major banks in Indonesia, which include Bank Rakyat Indonesia (BRI), Bank Central Asia (BCA), Bank Negara Indonesia (BNI), and Bank Mandiri. Data was taken from 1 June 2013 to 27 September 2022. Stock price modeling is done using four methods: ARIMA Box-Jenkins, RNN, GRU, and LSTM. Model 1 represents the classical statistical model, while the rest are Deep Learning models. These models are compared to see how the performance of the Deep Learning model and the classical model is commonly used in Econometrics.

3.5. Preprocessing Data

This quantitative study uses stock price data of BRI, BNI, BCA, and Bank Mandiri from Yahoo finance from June 1, 2013 to September 28, 2022 as research data. This sampling was purposive because the data was limited to four major micro banks in Indonesia during a particular period. Because of this limitation, this research only uses time series data that containing open, high, low, close, volume, and adjusted close data. The data inconsistent closing attributes in stock split and dividend events were removed, and the adjusted close was used as the target attribute. Then, the data was processed using R-software 4.2.3 and Microsoft Excel 2019 to visualize and describe the result.

Before conducting data analysis, data should be prepared according to needs. In this stage, the data is prepared and transformed using the Z transformation, according to equation, where μX is the average of the variables X and σX (Shumway & Stoffer, 2019). Data transformation is done to eliminate data units and make it easier for the model to perform computations because the data range is getting smaller, namely between -3 to 3 (Le et al., 2019).

$$Z_i = \frac{(X_i - \mu X \sigma)}{\sigma_x} \tag{4}$$

Deep learning is a part of machine learning research based on extracting features from data in greater detail. The way deep learning works is the result of replicating how the human brain works in sending information from one neuron to another. As a result, Deep learning can produce a high-level knowledge representation (Almalaq & Edwards, 2017; Najafabadi et al., 2015; Qin, 2019). The deep learning applications in this study, RNN, GRU, and LSTM modeling, use two hidden layers, with the number of nodes in each layer 128 and 64, respectively. In addition, the Activation Function used is the hyperbolic tangent function known as tanh, and the epoch used is 20.

This stude use Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) to evaluate the different performance indicators and develop a precise evaluation in Equation 5-7 (Wu et al., 2019):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}} \tag{5}$$

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n} \tag{6}$$

$$MAPE = \frac{\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|}{n} \times 100 \tag{7}$$

Where y_i is he actual stock price of the Banks, $\hat{y}_i$ is the predicted price of the Banks, and n is the predictive periode number. Models that have smaller RMSE, MAE, and MAPE tend to be more accurate in predicting a value.

4. RESULT

The stock characteristics of each bank from 1 June 2013 to 28 September 2022 are visualized through the line plot shown in Figure 4.

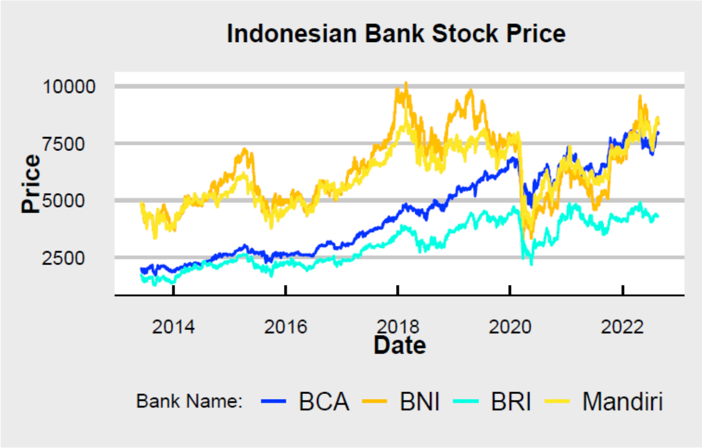

Fig. 4. Indonesia Bank Stock Price (Processed Primary Data, 2023)

The line plot shows the movement in the stock value of BRI, BCA, BNI, and Bank Mandiri. It can be seen that in the early 2020 period, all stock values fell drastically due to the Covid-19 pandemic, but the stock values gradually recovered over time. In general, at the beginning of the period, BRI and BCA were worth around Rp2,000, while BNI and Bank Mandiri were worth around Rp4,000. In the final period, the shares of BCA, BNI, and Bank Mandiri increased to Rp8,000. Meanwhile, BRI increased to Rp4,000. In addition, Figure 4 also shows that the price at the beginning of the observation period shows that BNI has the highest share price, followed by Bank Mandiri. At the same time, the lowest share price is owned by BRI. The economic conditions during the 2020 pandemic also affected the order of share prices for the four major banks in Indonesia.

This research also wants to show the performance of ARIMA Box-Jenkins modeling and deep learning through RMSE and forecasting results. ARIMA Box-Jenkins modeling on stock price data of the four major banks in Indonesia experiences white noise assumption violations. It further reinforces that ARIMA Box-Jenkins modeling still has deficiencies in overcoming nonlinear data characteristics. The performance of ARIMA Box-Jenkins, RNN, GRU, and LSTM modeling on the stock prices of BRI, BNI, BCA, and Bank Mandiri is shown through RMSE in Table 1.

Tab. 1. Model Evaluation of ARIMA Box-Jenkins, RNN, GRU, and LSTM (Processed Primary Data, 2023)

RMSE				
Model	**BRI**	**BNI**	**BCA**	**Mandiri**
ARIMA	0.069	0.084	0.040	0.089
RNN	0.156	0.163	0.148	0.165
GRU	0.153	0.158	0.140	0.157
LSTM	0.149	0.158	0.141	0.159
MAE				
Model	**BRI**	**BNI**	**BCA**	**Mandiri**
ARIMA	0.048	0.061	0.026	0.064
RNN	0.118	0.123	0.109	0.121
GRU	0.115	0.118	0.103	0.115
LSTM	0.113	0.118	0.103	0.116
MAPE				
Model	**BRI**	**BNI**	**BCA**	**Mandiri**
ARIMA	0.015	0.000	0.011	0.057
RNN	33.99	28.97	58.64	38.77
GRU	31.76	26.36	52.05	34.25
LSTM	31.85	27.81	57.65	36.06

From Table 1, it can be seen that the ARIMA Box-Jenkins modeling has the smallest RMSE, MAE, and MAPE at each stock price. However, the small error does not indicate the model's goodness if there are violated assumptions, namely white noise. The violation of this assumption was caused by extreme stock price fluctuations, especially during the early period of the Covid-19 pandemic. Therefore, ARIMA Box-Jenkins modeling is not suitable for this case.

RNN, GRU, and LSTM modeling are deep learning-based models, so no assumptions are needed. Among the three deep learning models, RNN has the highest RMSE value than the other two deep learning models. It is because the LSTM and GRU can mitigate the problem of missing gradients (Wei et al., 2021). In addition, the GRU and LSTM models have almost similar error evaluation results. In modeling Bank BRI stock prices, the smallest RMSE and MAE values occur in LSTM modeling. In modeling Bank BNI stock prices, the GRU and LSTM models provide the same RMSE and MAE values. In modeling Bank BCA stock prices, GRU has the smallest RMSE value and has the same MAE value as the LSTM model. While in modeling the stock price of Bank Mandiri, the GRU model has the smallest RMSE and MAE values. The inconsistency of error evaluation in the model is not a big problem if it has a very small difference. A different thing happens in the evaluation method with MAPE where all four stock price modeling has the smallest MAPE value in the GRU model.

The similarity of the performance of the GRU and LSTM models provides information that the prediction of Bank stock prices in Indonesia with the GRU or LSTM models will provide almost the same results. However, sometimes not only accurate prediction results need to be considered, but also related to the simplicity of the analysis method. In this study, the simplicity of the analysis method can be seen based on the number of parameters needed to form an accurate model as in Table 2.

Tab. 2. Total Parameters of RNN, GRU, and LSTM Model (Processed Primary Data, 2023

Model	Total Parameters
RNN	29
GRU	87
LSTM	116

Based on Table 2, we can see that the RNN model has the fewest parameters, so it is the simplest model. However, RNN has worse performance than the GRU and LSTM models. The GRU model as a prediction model for Bank stock prices in Indonesia with 87 parameters is less than the parameters in modeling with LSTM (114 parameters). Therefore, in terms of simplicity of the analysis method, the GRU model is superior to the LSTM model for predicting the stock prices of BRI, BNI, BCA, and Mandiri,

Therefore, in forecasting the stock prices of the four banks in Indonesia, GRU was determined to be the best model because the simplicity and the performance as parsimony principle (Ringmu & Oumar, 2022). The plot of the actual and predicted value of each bank modeled with GRU as the best model is shown in Figure 5.

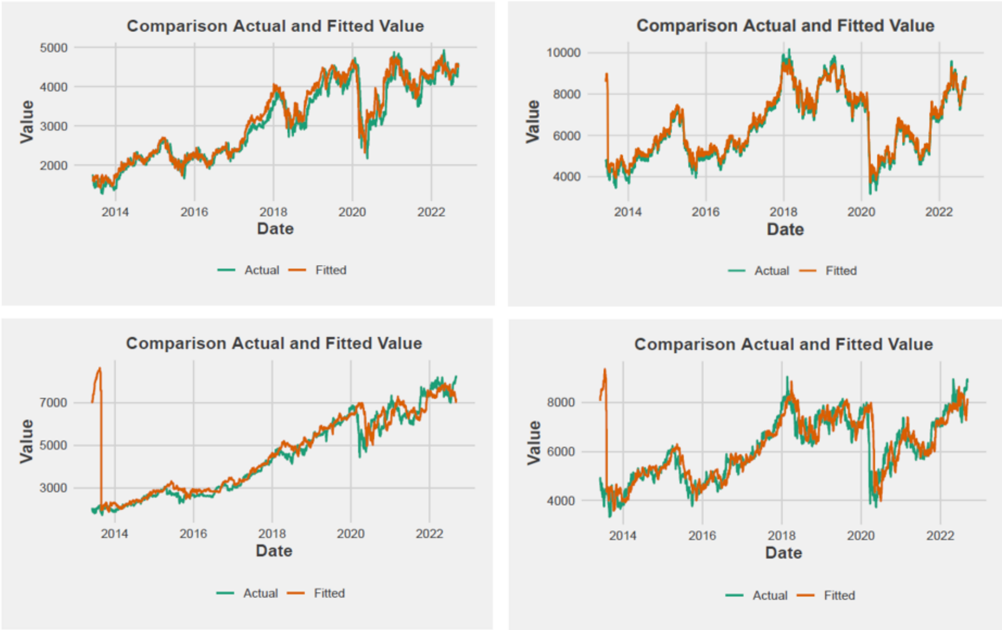

Fig. 5. Predicted Value and Actual Stock Privece of BRI (Top-Left), BCA (Top-Right), BNI (Bottom-Left), and Mandiri (Bottom-Right) (Processed Primary Data, 2023)

The model can detect data fluctuations; in the late 2017 period, the actual data moved up, and the model could also detect this movement. Likewise, stock movements fell drastically in the early 2020 period, which was the start of the Covid-19 pandemic. Also, during this period, the model can detect these extreme spikes. So, the model is suitable and feasible to use as forecasting.

Although ARIMA models are often used in time series analysis to predict stock prices, there are some scientific reasons that make them not always effective. One of them is the limitation of the ARIMA model in dealing with non-stationary data which requires the data to have constant mean and variance. Since stock price movements tend to be nonstationary and often experience sharp and unpredictable fluctuations, ARIMA models cannot handle nonstationary stock price movements. In addition, stock prices are also vulnerable to external factors such as political events, natural disasters, and unpredictable financial crises such as the COVID-19 pandemic which caused a drastic decline in the stock prices of BRI, BNI, BCA, and Mandiri. Therefore, the ARIMA model is unable to account for these external factors in predicting stock prices.

The results show that deep learning modeling is suitable for predicting the stock prices of 4 major banks in Indonesia. This is an advantage of machine learning that can handle non-linear data, which often occurs in stock prices. With this capability, machine learning can produce more accurate and reliable analysis in predicting stock prices.This study compares the prediction results of the RNN, LSTM, and GRU deep learning models. It can be concluded that the GRU model performs better. The results of this study are in line with research by (Qin, 2019), which compared deep learning models for predicting time series data in the Dissolved Oxygen Prediction case study. The results show that the GRU is better than the other models.

BRI, BNI, BCA, and Mandiri are included in the LQ45 index, which is a stock index consisting of 45 stocks with the largest liquidity and market capitalization on the Indonesia Stock Exchange (IDX) (IDX, 2023). Investing in bank stocks listed in LQ45 can be an attractive option for long-term investment as banking in Indonesia has a bright prospect with increasing economic growth. Therefore, modeling the stock prices of four major banks in Indonesia with GRU is very suitable given the advantages of GRU having long-term capabilities for help investment decision.

5. CONCLUSIONS

This research concludes that the ARIMA Box-Jenkins modeling is unsuitable for predicting BRI, BNI, BCA and Bank Mandiri stock prices. This is due to the data's nonlinear characteristics, which causes the assumption of white noise in the estimation of the ARIMA Box-Jenkins parameter to be violated. In addition, this study also compares the three deep learning models, RNN, LSTM, and GRU, on the stock price data of the four banks. The analysis results show that the GRU model generates the simpest model in the four Banks' stock price predictions. Therefore, GRU presented the best performance in the case of predicting the stock prices of BRI, BNI, BCA and Bank Mandiri.

Due to its frequent fluctuations, the stock market is a highly dynamic system. Predicting the stock market is a complex task that requires taking into account not only the prediction method but also the unique characteristics of individual stocks and the network system's ability to adapt to changing circumstances by retraining with new data. While our regularized GRU model shows higher prediction accuracy and faster convergence speed, its stability can be relatively poor at times. To address this issue, our next focus is on finding an optimization method that can improve the model's stability.

Conflicts of Interest

The authors declare there are no conflicts of interest regarding this article. The author alone are responsible for the content and writing article

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