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Optimizing Banking Stock Price Prediction: Deep Learning Based Approach

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Abstract :*Recently, the stock market has experienced significant instability, especially during the global pandemic which resulted in unprecedented economic impact. The main focus of this research is to develop an optimal prediction model using deep learning techniques for the projection of closing prices of bank stocks during the pandemic period. This study evaluates the performance of banking stocks, specifically ARTO, BRIS, BBNI, and BMRI in the Jakarta Composite Index (JCI). Data was extracted from Yahoo Finance and processed through LSTM and GRU algorithms, including data cleaning, normalisation, and descriptive statistical analysis. Scoring metrics such as MSE, RMSE, and MAPE are used to measure the effectiveness of the predictive models. The results show that the LSTM and GRU models can predict stock prices well. These findings provide a basis for trading strategies and improved decision-making in the stock market. Recent research confirms the importance of integrating deep learning methods such as LSTM and GRU in stock price prediction, helping to understand complex financial market fluctuations and improve prediction accuracy.*

Keywords: *Stock, Bank, Prediction, Stock Prediction, Deep Learning*

INTRODUCTION

In recent years, the stock market has witnessed extraordinary financial turmoil, especially during the pandemic that hit the world. The global pandemic has triggered an unprecedented global economic response, affecting various sectors, including the banking sector. As a crucial element in the economic structure, the banking sector is at the center of attention in facing a significant decline in the value of its shares (Agustina et al., 2022). This condition not only reflects uncertainty but also poses a serious challenge to the sustainability and stability of the global economy.

The regulatory and supervisory authority in the financial sector, known as the Financial Services Authority (OJK), indicated that the impact of the COVID-19 pandemic on the financial sector, especially on the Composite Stock Price Index (IHSG), was very significant. At the beginning of 2020 until March 20 2020, which only covers three months, the IHSG experienced a drastic decline from the level of 6,300 to 3,900. Along with the decline in the JCI, transaction volume also experienced a marked decline. If in 2019, transaction volume reached 36,534,971,048, in 2020 it decreased to 27,495,947,445. This phenomenon reflects the "wait and see" attitude of most investors who are worried about future market conditions. At that time, investor panic was further exacerbated by the emergence of new variants of the COVID-19 virus, such as Delta which was first discovered in mid-2021, followed by the Omicron variant at the end of 2021 to early 2022. The question is, what factors have a significant impact on the capital market, especially during the COVID-19 pandemic period? Several studies have investigated the dynamics of the relationship between the COVID-19 virus and capital markets in various countries. The data show us that ARTO, BRIS, BBNI, and BMRI as the top two highest and lowest stocks.

Apart from the study Phan & Narayan (2020) regarding the response of capital markets and countries to COVID-19, they present the argument that every time an unexpected event is announced, the market will provide an observable reaction. This is in line with the government's response to the global pandemic. Then, the study carried out by Haldar & Sethi (2021) state that market speculation has an impact on capital market fluctuations. Their findings show that news related to COVID-19 also plays a significant role in capital market dynamics. Furthermore, research by Rizvi et al. (2021) explore the market response to monetary and fiscal stimulus in four ASEAN member countries, namely Indonesia, Malaysia, Singapore and Thailand, as a result of the impact of the COVID-19 pandemic. They conclude that monetary policy takes time to have an impact on stock market conditions, while fiscal policy can act as a cushion to reduce the adverse impact of the pandemic on capital markets.

From this description, three key factors can be seen that influence the capital market. First, the policy stimulus implemented by the government and central bank. In the realm of monetary policy, the central bank implements quantitative easing by purchasing government securities, which has the potential to affect the performance of the country's capital markets. Meanwhile, the government's fiscal stimulus policy, in the form of assistance to businesses, also played a significant role. Second, speculation and news related to COVID-19 which affects the capital market. The uncertainty of the pandemic conditions encourages investors to speculate on the Indonesian capital market. Apart from that, news related to COVID-19 also contributes to shaping current and future market movements. Third, the government's response to the pandemic situation. Government actions regarding the pandemic also play a crucial role in influencing the condition of a country's capital markets, considering that the government's response will influence the prospects for economic recovery in the future.

Although there has generally been a decline in the banking stock market during the pandemic, this research notes a unique phenomenon. Two bank stocks recorded performance that was still burning at the peak, while two other stocks experienced severe declines (Permana et al., 2022). This raises in-depth questions about the factors that might influence the performance of certain bank shares in crisis conditions such as a pandemic. By exploring this phenomenon comprehensively, this research aims to develop an optimal predictive model to project closing stock prices, especially for two prominent bank stocks and two stocks that experienced significant declines during the pandemic. The deep learning approach used in this research seeks to increase the accuracy of stock market predictions, thereby providing a more solid basis for future investment decisions (Liu et al., 2022). Effective implementation of predictive models can provide significant benefits in managing risk and optimizing potential profits in banking stock investments. It is hoped that the results of this research will provide investors, financial analysts and strategic decision makers with a sharper view in understanding stock market dynamics during the global economic crisis. Determining share prices depends on the balance between supply and demand, so it is normal for there to be upward or downward fluctuations in share value.

Predictive analysis from financial experts provides an overview of future developments, including information related to stock prices (Prayogi, 2021). Before making an investment, investors have the opportunity to utilize the guidance provided by predictive analysis. If the information conveyed by predictive analysis reflects the company's economic conditions positively, this can attract investors' interest in investing, which then has an impact on increasing share value. On the other hand, if analyst predictions show signs of a recession in the company, investors tend to sell their shares, so that share prices will decline (Maghriby & Irawan, 2023). The link between analyst predictions and stock value is strengthened by studies(Yahaya, 2021), which highlights the impact of institutional trading and predictive analysis on stock market dynamics. Research results obtained by (Niederhoffer & Regan, 2018) shows that share values are strongly affected by changes in earnings, both absolutely and relative to analyst predictions (Suzuki et al., 2022). The findings indicate that there is a strong and significant relationship between errors in predictions and subsequent movements in stock prices. Based on the literature review above, it is hoped that this research can fill the knowledge gap by providing new insights into the factors that influence bank stock performance during the pandemic. By using a deep learning approach, this research goes further than commonly used analytical methods, with the hope of making a significant contribution to the literature on financial management and stock market prediction, especially in situations of global economic uncertainty.

LITERATURE REVIEW

Previous research conducted in deep learning with LSTM and GRU modeling includes (Nilsen, 2022). In that research, a comparison was made between the use of LSTM (Long Short-Term Memory), GRU (Gated Recurrent Unit), and RNN (Recurrent Neural Network) models in predicting stock prices in the LQ45 index. The comparison resulted in the best modeling being done by GRU with the highest accuracy value of 52% and an RMSE value of 202.3475, MSE value of 120380.1, and MAE value of 146.0420626. In a study by (Khalis Sofi et al., 2021), the Linear Regression, LSTM, and GRU algorithms were compared in predicting the stock prices of KEJU, and the GRU algorithm was found to be the best with an RMSE value of 0.034, MSE value of 0.001, and MAE value of 0.024. Another study conducted by (Sethia & Raut, 2019) compared the Supper Support Vector Machines (SVM), Multiple Layer Perceptron (MLP), GRU, and LSTM models in predicting stock prices. In this comparison, the LSTM model had the highest accuracy among the other models with an R2 score of 0.9486. There was also a study by (Idham et al., 2022) that developed a method for predicting prices using transformers in LSTM and GRU, resulting in an accuracy value of 0.394 for LSTM and 0.216 for GRU. Furthermore, in a study by (Meriani & Rahmatulloh, 2024), a comparison was made between the GRU and LSTM models in predicting the movement of gold prices. In this model, GRU proved to be more accurate than LSTM, although LSTM had lower error evaluation metric values with an MAE value of 0.0389, RMSE value of 0.0475, and MAPE value of 5.2047%, while the GRU model had an MAE value of 0.0447, RMSE value of 0.0545, and MAPE value of 6.0688%. Various studies have shown that in predicting time series data, LSTM (Long Short-Term Memory) and GRU (Gated Recurrent Unit) models have demonstrated high accuracy values. With the capabilities of LSTM and GRU, it is proven that both models can be used in this research to predict stock prices in the banking world.

RESEARCH METHODS

The first approach in this research involves a comprehensive selection of subjects and objects, namely banking shares listed in the Composite Stock Price Index (IHSG). With full consideration of the context of the ongoing phenomenon, the stocks selected as research samples were ARTO, BRIS, BBNI, and BMRI, respectively are the top and bottom two stocks in the global pandemic period. This sample selection was carried out carefully through a purposive sampling method, aiming to formulate a focused model design focus in the context of this research (Robinson, 2022).

Data collection was carried out through a reliable source, namely Yahoo Finance, with reference to the stock market closing time range from the date December 31, 2018 until date December 29, 2023. The data analysis technique applied involves the concept of deep learning, it is hoped that it can produce data that is not only valid and reliable, but also able to create an adequate predictive model in predicting banking stock market movements (Sonkavde et al., 2023). In addition, this research strictly follows the applicable research ethics code, ensuring the integrity and credibility of the entire research process.

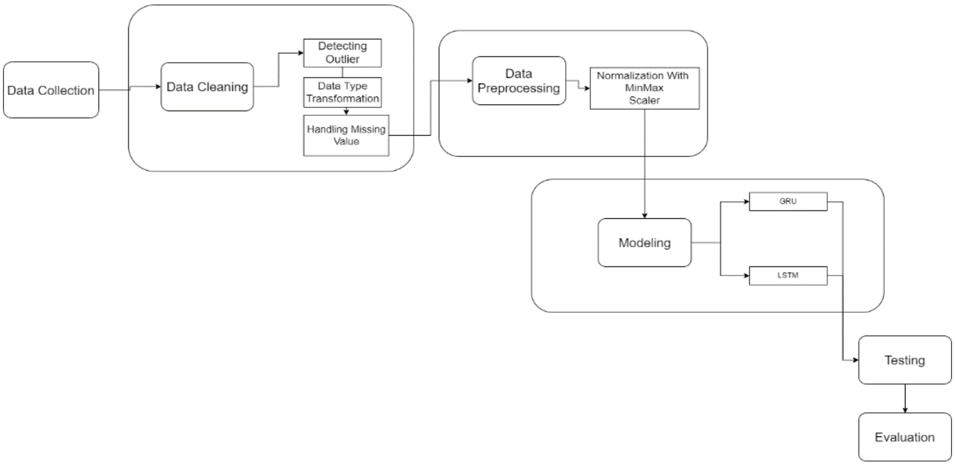

Figure 1. Research Methodology
Source: Authors, 2024

In this research, data analysis is a very important first step. This stage prepares the data before proceeding to the next stage. A share data ARTO, BRIS, BBNI, and BMRI used in this research is tabular data in numeric form with float (decimal) data type. Data that has been successfully loaded will be processed with descriptive statistical analysis to show the mean and standard deviation of each data. The mean, or average, is one of the main indicators used in this analysis (Syahfitri et al., 2023). By involving the mean in descriptive statistical analysis, this research can provide a better understanding of the characteristics of ARTO, BRIS, BBNI and BMRI stock data. Additionally, averages can also be used as a means of comparison between two or more data sets, allowing researchers to evaluate differences and similarities among observed variables.

$$\bar{x} = \frac{x1 + x2 + x3 + \ldots + xn}{n} \quad \ldots\ldots 1$$

Information: $\bar{x}$ = Mean; $x1$, $x2$, ..., xn = 1st, 2nd, ..., nth Data, n = Total Data

Standard deviation also plays a role in doing so by analyzing descriptive statistics to show how far the data is spread from the average value (mean). It is important to note that standard deviation not only provides information about the distribution of data, but can also be used to assess whether the data distribution is normal or not.(Pradana, 2017). In the context of ARTO, BRIS, BBNI, and BMRI stock predictions, standard deviation analysis can provide insight into the rate of change in stock prices over time. This can be an important consideration for investors or analysts in measuring the level of risk associated with investing in these shares.

$$\sigma = \sqrt{\Sigma(X - \mu)^2/n} \quad \ldots\ldots 2$$

Information: σ = Population standard deviation; X = Middle value; μ = Average value; n = Number of data

Data that has undergone descriptive analysis is continued into the data cleaning process to identify and correct incomplete and less relevant data from several existing data sets. In the data cleaning process carried out in this research, outlier detection and missing value handling were implemented. Outliers are data values that experience deviations from another set of data. Outliers can influence the modeling that will be carried out and can influence the data analysis process(Nirad & Surendro, 2018). Therefore, it is necessary to detect outliers and remove outliers in order to get more accurate predictions. Several existing methods for detecting outliers in this research use methodsIQR (Interquartile Range) by finding the first and third quartiles (Q1 & Q3) then calculating the IQR value by subtracting Q1 and Q3(Sihombing et al., 2023). Study(Siringoringo et al., 2022) carrying out the IQR method to handle outliers produces outlier values that experience shrinkage.

$$IQR = Q3 - Q1 \quad (3)$$

Not only outliers can influence data analysis but also missing values. Missing value is a collection of data that is incomplete and missing (Herliani & Kudus, n.d.). The approach that can be used to deal with missing values is data imputation. This imputation approach is used by filling in data that has missing values (Ilham, 2020). The imputation carried out in this study used mean imputation (average). This method was carried out by filling in the missing values using the average value of the variable. This is done because the data used to predict ARTO, BRIS, BBNI and BMRI share prices are numbers. With a small amount of missing data, imputation of the mean becomes an option in dealing with missing values in the data (Wilsen et al., 2018).

Data that has gone through the data cleaning process will enter the preprocessing stage, which is the step of changing raw data into data that is easy to understand and process by computers. The preprocessing step in this research is data normalization using Min-Max Scaler, this aims to carry out linear transformations using minimum and maximum values (Pratama et al., 2022). On research (Suryanegara & Purbolaksono, 2021) using the Min-Max Scaler in the normalization stage by getting the highest accuracy value in the modeling carried out at 95.45%, this has become a reference for researchers in using the Min-Max Scaler in preprocessing data normalization.

$$Xsc = \frac{X - Xmin}{Xmax - Xmin} \quad (4)$$

In predicting these stocks, a deep learning approach is used which utilizes a layered artificial neural network for multiple non-linear transformations (Nugroho et al., 2020). Deep learning can be said to be a combination of machine learning and artificial neural networks. LSTM (Long Short-term Memory) and GRU (Gated Recurrent Unit) is the modeling used in the deep learning approach in predicting stock prices. LSTM is a modification in the recurrent neural network section with the addition of memory cells to store information (Fadli & Km, n.d.). LSTM has three gates, namely input gate, forget and output gate.

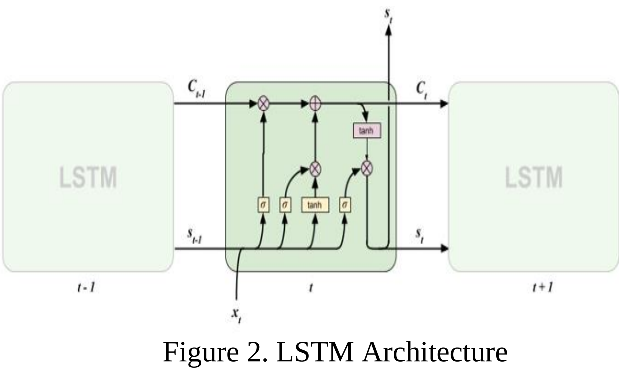

Figure 2. LSTM Architecture
Source: Karyadi, 2022

One type of well-known LSTM derivative algorithm is GRU. GRU has the advantage of being computationally simpler than LSTM, but has an equivalent level of accuracy (Karno et al., 2020)

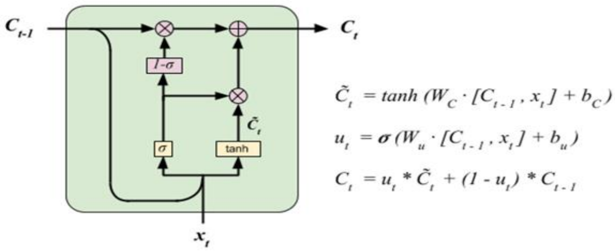

Figure 3. GRU Architecture
Source: Karyadi, 2022

Previous research that used the LSTM and GRU algorithms in developing stock predictions and determining the best performance included (Khalis Sofi et al., 2021) managing public data in the form of generating time series mark RMSE, MSE, and MAE are 0.034 for RMSE, 0.001 for MSE and MAE is 0.024. Meanwhile, the RMSE, MSE, and MAE values using LSTM are 0.048, 0.002, and 0.038. The lower the RMSE, MSE, and MAE values, the higher the level of algorithm performance. In research (Idham et al., 2022), the accuracy level of the LSTM algorithm is 0.394 and GRU is 0.216. This makes the use of the LSTM and GRU algorithms in predicting stock prices have a high level of performance.

In the final stage of stock prediction, you need to go through the evaluation stage. The evaluation stage is used to measure the performance of the models used, namely LSTM and GRU using the MSE, RMSE and MAPE evaluation matrices. The smaller the MSE (Mean Squared Error) value, the better the model performance.

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (yi - \hat{y}i)^2 \text{.......} 5$$

RMSE (Root Mean Squared Error) is the square root of MSE also used for predictions in the same units as the target variable (Maulana et al., 2024).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (yi - \hat{y}i)^2} \text{.......} 6$$

MAPE (Mean Absolute Percentage Error) is the average value of the absolute value and predicted value. Using MAPE you can see the evaluation value of the predictions that have been made (Nabillah & Ranggadara, 2020). Likewise with MSE and RMSE, the smaller the MAPE value will be produce modeling which has a high level of accuracy.

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \frac{yi - \hat{y}i}{and} \text{ x } 100\% \text{.......} 7$$

RESULTS AND DISCUSSION

The population in this study focuses on data on two bank stocks that have increased, namely PT Bank Jago Tbk (ARTO) and PT Bank Syariah Indonesia (BRIS) and two bank stocks that have decreased, namely PT Bank Negara Indonesia (Persero) Tbk (BBNI) and PT Bank Mandiri (Persero) Tbk (BMRI). The four populations used in this study are types of banking stocks that are listed on the Indonesia Stock Exchange (IDX) and the data used is also public data with several attributes/variables it has. The focus of the research on this data is to predict the value of the closing stock price (close) in the last five years (31 December 2018 to 29 December 2023) with data that has been collected from the Yahoo Finance page.

Table 1. Close Price at Each Bank

Date	Close Price			
	ARTO	BRIS	BBNI	BMRI
2018-12-31	184.0	525.0	4400.0	3687.5
2019-01-01	184.0	525.0	4400.0	3687.5
2019-01-02	188.0	520.0	4362.5	3662.5
...	...	...	...	...
2023-12-27	2970.0	1695.0	5275.0	6000.0
2023-12-28	2940.0	1740.0	5350.0	6125.0
2023-12-29	2900.0	1740.0	5375.0	6050.0

Source: Yahoo Finance (2024)

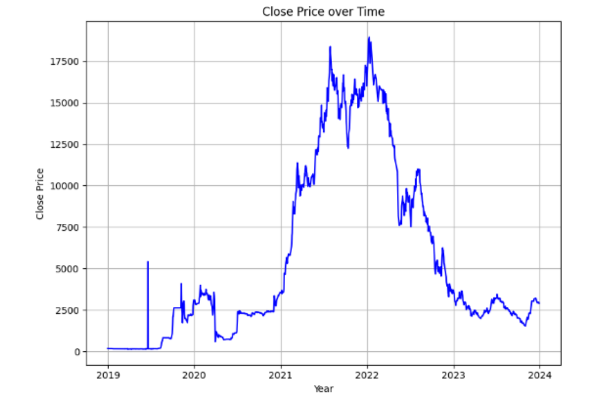

Figure 4. ARTO Close Price

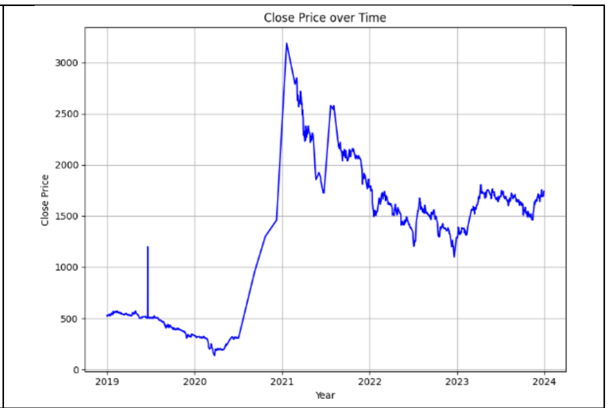

Figure 5. BRIS Close Price

Figure 6. BBNI Close Price

Figure 7. BMRI Close Price

Source: Authors Data, 2024

From Table 1, it can be seen that the existing data shows an increase from the beginning to the end of the data collected. However, when looking at the visualization of some of the figures above, the fact is that not all existing data shows an increase during the pandemic (end of 2019 to 2020). In Figure 4 and Figure 5 are graphs of the closing prices of ARTO and BRIS bank shares where indeed during this period there was an increase in stock prices. However, something different happened to the shares of BBNI and BMRI banks as shown in Figure 6 and Figure 7 where during this period they experienced a decline. Some of these things make this research try to present a prediction model with a deep learning approach to anticipate and preventive action in providing accurate prediction results. This is also certainly in line with research (Widiputra & Juwono, 2024) that a successful approach to forecasting time series involves the utilization of deep learning models, which prove their effectiveness with the ability to automatically understand complex patterns in data, something that may be difficult to identify using traditional statistical methods.

Descriptive statistical analysis on the closing price variable of bank stock data for ARTO, BRIS, BBNI, and BMRI is based on the minimum, maximum, average, and standard deviation values described in Table 2 below.

Table 2. Statistical Descriptive Analysis

Indicator	Close Price			
	ARTO	BRIS	BBNI	BMRI
Minimum	145.0	135.0	1580.0	1860.0
Maximum	18950.0	3190.0	5375.0	6125.0
Mean	5413.831	1200.18211	3750.439984	3904.502841
Standard Deviation	5250.811871	675.61032	904.456984	978.628033

Source: Authors Data (2024)

The results of the descriptive statistical analysis as contained in Table 2, show that there is a significant value between the minimum and maximum value differences. It also appears that there is a minimum or maximum value that is far from the average value and standard deviation. Of course, this further strengthens that at this time, the data related to bank shares experienced a very drastic decline or increase and needed the right approach.

Initially, bank stock data, be it ARTO, BRIS, BBNI, or BMRI, have problems that need to be overcome to ensure that the data is completely clean before modelling to make predictions. Among them, there are several treatments in data cleaning such as outlier detection and handling missing values. Outlier detection is done to check the distribution of existing data in terms of the gap between existing values. Then in dealing with empty/missing values, the data imputation method is carried out with the average value, this was chosen based on the existing data being numerical data. The problems in this data have been overcome and resolved with these steps, so then the data has been declared feasible for further modelling to make predictive results.

Based on the graph visualization in Figures 4, 5, 6, and 7, it shows that the bank stock data has a significant gap or a considerable difference between one value and another. In this regard, deep learning models usually need to normalize data to produce accurate predictions and minimize errors. MinMax Scaler is one of the normalization methods that will be used in this research. The following table illustrates the data before and after normalization.

Table 3. Data Before and After Normalization

Date	Close Price							
	ARTO		BRIS		BBNI		BMRI	
	Before	After	Before	After	Before	After	Before	After
2018-12-31	184.0	0.00207392	525.0	0.12765957	4400.0	0.743083	3687.5	0.42848769
2019-01-01	184.0	0.00207392	525.0	0.12765957	4400.0	0.743083	3687.5	0.42848769
2019-01-02	188.0	0.00228663	520.0	0.12602291	4362.5	0.73320158	3662.5	0.42262603
...	...	...	...	...	...	...	...	...
2023-12-27	2970.0	0.150226	1695.0	0.5106383	5275.0	0.97364954	6000.0	0.97069168
2023-12-28	2940.0	0.14863068	1740.0	0.52536825	5350.0	0.99341238	6125.0	1
2023-12-29	2900.0	0.14650359	1740.0	0.52536825	5375.0	1	6050.0	0.98241501

Source: Authors Data (2024)

It can be seen that in Table 3, the existing data has been normalized by making the values in the data in the range of 0 (zero) to 1 (one) according to the existing calculation method. The normalized data will then be used as training data in modelling using the deep learning approach.

The next stage is modelling using deep learning approach. There are two models or algorithms that will be used in predicting stock prices based on bank stock price data that has been processed previously. The two models that will be used include Long Short Term Memory (LSTM) and Gated Recurrent Unit (GRU). The selection of these two models is based on the suitability and accuracy of their performance in handling data with time series properties, especially in the context of stock price prediction. Then from the data, it is determined how the parameter settings must be prepared. The following are the parameters required in the LSTM and GRU models. Parameter initialization in the LSTM and GRU models consists of several layers as summarized in Figure 8 and Figure 9 below.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 lstm (LSTM)                 (None, 1, 64)             16896

 dropout (Dropout)           (None, 1, 64)             0

 lstm_1 (LSTM)               (None, 1, 64)             33024

 dropout_1 (Dropout)         (None, 1, 64)             0

 lstm_2 (LSTM)               (None, 1, 64)             33024

 dropout_2 (Dropout)         (None, 1, 64)             0

 lstm_3 (LSTM)               (None, 64)                33024

 dropout_3 (Dropout)         (None, 64)                0

 dense (Dense)               (None, 1)                 65

=================================================================
```

Figure 8. LSTM Modelling

```
Model: "sequential_1"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 gru (GRU)                   (None, 1, 64)             12864

 dropout_4 (Dropout)         (None, 1, 64)             0

 gru_1 (GRU)                 (None, 1, 64)             24960

 dropout_5 (Dropout)         (None, 1, 64)             0

 gru_2 (GRU)                 (None, 1, 64)             24960

 dropout_6 (Dropout)         (None, 1, 64)             0

 gru_3 (GRU)                 (None, 64)                24960

 dropout_7 (Dropout)         (None, 64)                0

 dense_1 (Dense)             (None, 1)                 65

=================================================================
```

Figure 9. GRU Modelling

Source: Authors Data, 2024

After building the architecture in both types of models, LSTM and GRU, then training data will be carried out using an epoch value of 100. In line with the results of research conducted in (Rasyid et al., 2021), the epoch value of 100 is considered to provide the smallest or most effective MSE value in testing model performance.

After making the model architecture and training data, the next step is testing the model by displaying the predicted bank stock prices from ARTO, BRIS, BBNI, and BMRI which will be compared with the actual data. The results regarding predicted data and actual data from the LSTM model can be seen in the following table.

Table 4. Prediction Results of the LSTM Model

Date	Close Price							
	ARTO		BRIS		BBNI		BMRI	
	Actual	Predict	Actual	Predict	Actual	Predict	Actual	Predict
2018-12-31	184.0	457.46112	525.0	546.1174	4400.0	4387.818	3687.5	3634.3857
2019-01-01	184.0	457.46112	525.0	546.1174	4400.0	4387.818	3687.5	3634.3857
2019-01-02	188.0	460.60822	520.0	541.7547	4362.5	4350.1147	3662.5	3609.4321
...	...	...	...	...	...	...	...	...
2023-12-27	2970.0	2830.969	1695.0	1699.165	5275.0	5114.3853	6000.0	5793.628
2023-12-28	2940.0	2803.508	1740.0	1745.5552	5350.0	5157.683	6125.0	5869.659
2023-12-29	2900.0	2766.9556	1740.0	1745.5552	5375.0	5171.2856	6050.0	5824.941

Source: Authors Data (2024)

Based on the prediction results using the LSTM model as shown in Table 4, it appears that some predicted data have higher values than actual data or vice versa. The value of the prediction results can also be said to be almost close to the actual data. Then also to see an overview of the comparison of actual data and stock prediction data for the four banks using the LSTM model, there is the following figure.

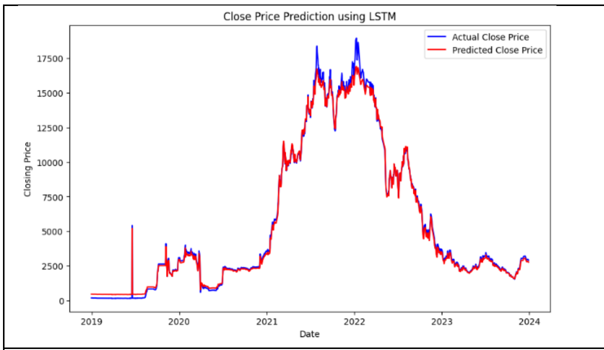

Figure 10. LSTM Prediction (ARTO)

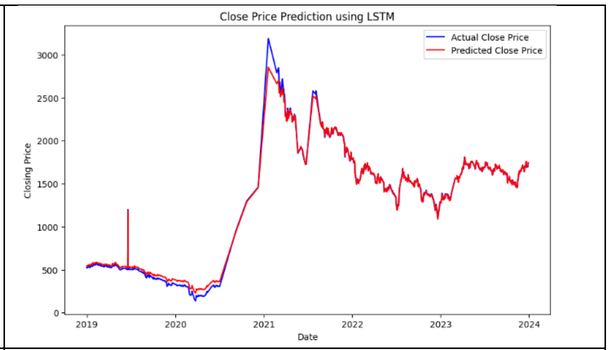

Figure 11. LSTM Prediction (BRIS)

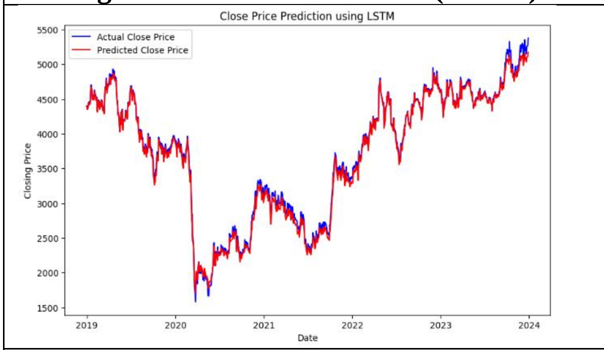

Figure 12. LSTM Prediction (BBNI)

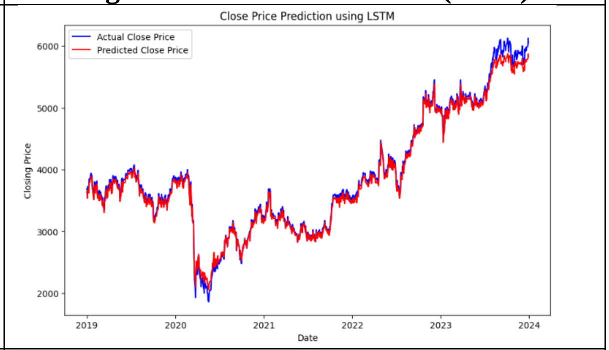

Figure 13. LSTM Prediction (BMRI)

Source: Authors Data, 2024

At a glance at Figures 10, 11, 12, and 13 above, it can be seen that the predicted value symbolized by the red line can be said to be almost close to the actual value of the data symbolized by the blue line, and there is still a slight gap between the two. This proves that the LSTM model is one of the deep learning models that is quite feasible in helping to provide predictive results on stock prices.

Then the second model tried in this study is the GRU model. The results of the predicted value compared to the actual value in the data are in the table below.

Table 5. Prediction Results of the GRU Model

Date	Close Price							
	ARTO		BRIS		BBNI		BMRI	
	Actual	Predict	Actual	Predict	Actual	Predict	Actual	Predict
2018-12-31	184.0	323.07608	525.0	543.8785	4400.0	4430.03	3687.5	3705.777
2019-01-01	184.0	323.07608	525.0	543.8785	4400.0	4430.03	3687.5	3705.777
2019-01-02	188.0	326.29858	520.0	538.87213	4362.5	4392.6187	3662.5	3681.0754
…	…	…	…	…	…	…	…	…
2023-12-27	2970.0	2756.8528	1695.0	1751.3053	5275.0	5280.2256	6000.0	5845.1694
2023-12-28	2940.0	2728.6567	1740.0	1797.67	5350.0	5350.609	6125.0	5920.1265
2023-12-29	2900.0	2691.1274	1740.0	1797.67	5375.0	5373.9683	6050.0	5876.061

Source: Authors Data (2024)

Based on the prediction results in Table 5 above using the GRU model, it appears that there are some predicted data that the majority have higher values than actual data, but there are also lower predicted values. The value of the prediction results can also be said to be almost close to the actual data. An overview of the comparison of actual data and stock prediction data for the four banks using the GRU model, can be seen in the following figure.

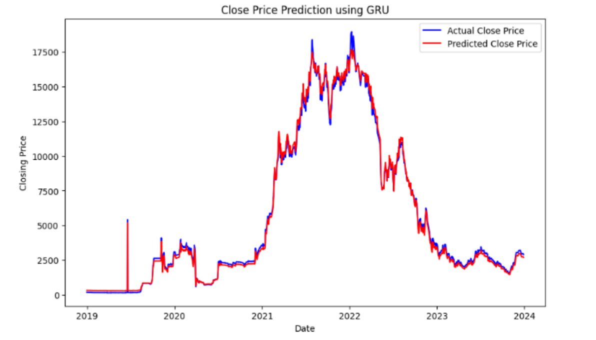

Figure 14. GRU Prediction (ARTO)

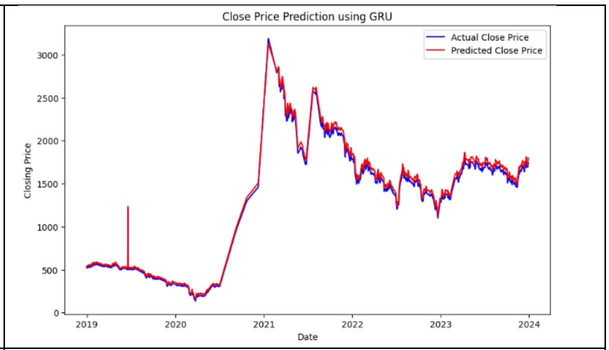

Figure 15. GRU Prediction (BRIS)

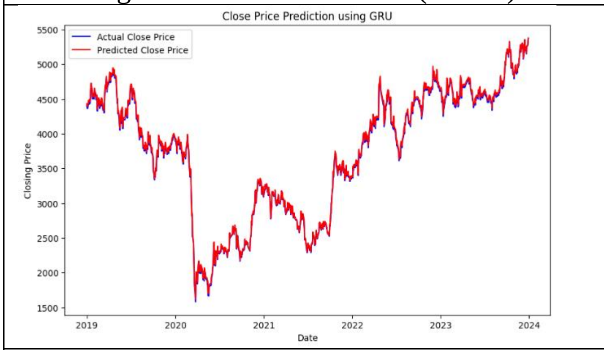

Figure 16. GRU Prediction (BBNI)

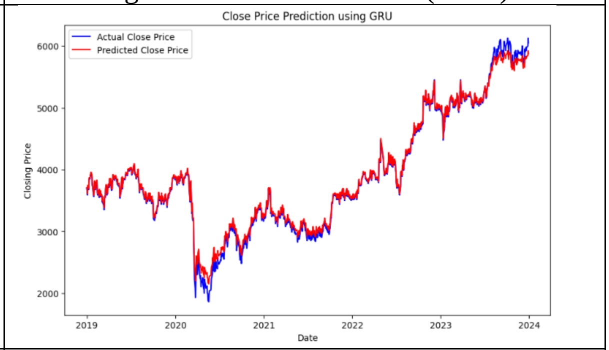

Figure 17. GRU Prediction (BMRI)

Source: Authors Data, 2024

In looking at Figures 14 to 17 above, it can be seen that the predicted value shown by the red line is almost close to the actual value in the data shown by the blue line. Although there is a slight difference between the two, this indicates that the GRU model can also be considered a viable deep learning model in providing good predictions for stock price prediction.

To test the extent of the effectiveness of the two deep learning models used, a model evaluation will be conducted next. The model is evaluated using several indicators ranging from MSE, RMSE, and MAPE according to the existing calculation method. The smaller the MSE, RMSE, and MAPE values, the better and more accurate the model will be in producing predictive values. The results of the model evaluation on the use of both models and from four types of bank stocks are in the following table.

Table 6. LSTM Model Evaluation

Indicator	**LSTM Model Evaluation**			
	ARTO	**BRIS**	**BBNI**	**BMRI**
MSE	0.000185	0.000108	0.000193	0.000276
RMSE	0.013615	0.010404	0.013898	0.016614
MAPE	2.584471e+07	3.173783e+07	2.844525e+07	3.755514e+07

Source: Authors Data (2024)

Table 7. GRU Model Evaluation

Indicator	**GRU Model Evaluation**			
	ARTO	**BRIS**	**BBNI**	**BMRI**
MSE	0.000147	0.000200	0.000037	0.000250
RMSE	0.012110	0.014127	0.006102	0.015823
MAPE	1.345329e+07	9.259082e+06	9.192906e+06	5.527444e+07

Source: Authors Data (2024)

Several things can be highlighted from the model evaluation results of both LSTM in Table 6 and GRU in Table 7. The first is in ARTO bank shares where the MSE, RMSE, and MAPE values in the GRU model are lower so that for ARTO bank stock data it can be said that it is more effective to use the GRU model than LSTM. Then if in BRIS bank shares the MSE and MSE values in the LSTM model are smaller while the MAPE value in the GRU model is smaller so that in this BRIS bank stock data both are also considered feasible. Furthermore, in BBNI bank stocks it appears that the MSE, RMSE, and MAPE values in the GRU model are smaller than LSTM so that the GRU model is also considered more effective. Similar to other bank stocks, BMRI bank stocks also have lower MSE and RMSE values in the GRU model but have a higher RMSE, this also proves that both models are also said to be feasible in predicting stock prices.

From the prediction results that have been carried out using a deep learning approach in this study, it proves that from the results of the evaluation of the LSTM and GRU models on the prediction of bank stock prices ARTO, BRIS, BBNI, and BMRI show variations in the effectiveness of both. Even the same thing has also been proven through research Alzaman, (2024) that the results show promising portfolio returns 20% better than the market in general. Research by Beniwal et al., (2024) also shows the potential of deep learning models for long-term stock price forecasting and can help in building trading and risk management decision-making systems. This further indicates that both deep learning models used in this study can be considered feasible and effective in predicting stock prices, although their relative effectiveness may depend on the bank stocks evaluated. The use of deep learning models, such as LSTM and GRU, in stock price prediction has the potential to make an important contribution to investment decision-making in the banking sector, helping investors and financial practitioners to anticipate market changes and optimized their investment strategies.

CONCLUSION

The limitation of this study is the reliance on graphical data trends for model analysis. Not all individuals possess the skills to interpret graphic data effectively, highlighting a practical challenge. Additionally, the model's performance is influenced by specific characteristics of the stock price data, emphasizing the importance of tailoring the model to the unique features of the data. Besides that, the data for analyzing just using four stocks in banking. So, this will be cannot generalize for data analysis in the banking sector.

The findings suggest that both LSTM and GRU models offer potential benefits in improving stock price predictions for banks like ARTO, BRIS, BBNI, and BMRI. The GRU model, in particular, demonstrates a capacity for understanding intricate patterns in historical stock price data, as reflected in lower error rates. The application of these models in the economic and banking sectors has the potential to enhance the quality of stock price predictions, facilitating more informed investment decisions and contributing to intelligent decision-making within the financial industry. It is crucial to consider the specific characteristics of individual banks and market conditions, continuing to refine evaluation methods for the effective implementation of these models amidst dynamic challenges in the economic landscape.

LIMITATIONS AND RECOMMENDATION

Limitations of this study include the dependency on specific characteristics of stock price data, as the effectiveness of the model may vary with different data sets. The complex structure of LSTM compared to GRU adds a layer of consideration in evaluating model performance. In predicting stock prices for ARTO, BRIS, BBNI, and BMRI banks, both LSTM and GRU models exhibit variations in predictive outcomes. Generally, the results indicate that the GRU model demonstrates a potential for lower error rates in MSE, RMSE, and MAPE indicators, suggesting its proficiency in deciphering intricate patterns in historical stock price data. Implications of these models in economics and banking lie in their potential to enhance stock price predictions, facilitate more informed investment decisions, and contribute to intelligent decision-making in the financial sector. However, it is crucial to account for the distinct characteristics of individual banks, market conditions, and continuously develop comprehensive evaluation methods to ensure the models' effective application amidst the dynamic challenges in the economic landscape.

REFERENCES

Agustina, N., Hariyani, D., Widiasmara, A., & Jarwa, T. (2022). Efek New Normal Terhadap Harga Saham dan Volume Transaksi. *Akuntansi : Jurnal Akuntansi Integratif*, *8*(1). https://doi.org/10.29080/jai.v8i1.871

Alzaman, C. (2024). Deep learning in stock portfolio selection and predictions. *Expert Systems with Applications*, *237*, 121404. https://doi.org/10.1016/j.eswa.2023.121404

Beniwal, M., Singh, A., & Kumar, N. (2024). Forecasting multistep daily stock prices for long-term investment decisions: A study of deep learning models on global indices. *Engineering Applications of Artificial Intelligence*, *129*, 107617. https://doi.org/10.1016/j.engappai.2023.107617

Fadli, H. F., & Km, J. K. (n.d.). *Identifikasi Cyberbullying pada Media Sosial Twitter Menggunakan Metode LSTM dan BiLSTM*.

Haldar, A., & Sethi, N. (2021). The news effects of COVID-19 on global financial market volatility. *Buletin Ekonomi Moneter Dan Perbankan*, *24*, 33–58. https://doi.org/10.21098/bemp.v24i0.1464

Herliani, F. D., & Kudus, A. (n.d.). *Penanganan Data Missing dengan Algoritma Multivariate Imputation By Chained Equations (MICE)*.

Idham, I., Ghudafa Taufik Akbar, M., Panggabean, S., & Noor, M. (2022). Perbandingan Prediksi Harga Saham Dengan Menggunakan LSTM GRU Dengan Transformer. *Smart Comp: Jurnalnya Orang Pintar Komputer*, *11*(1), 44–47. https://doi.org/10.30591/smartcomp.v11i1.3185

Ilham, A. (2020). *hybrid Metode Boostrap Dan Teknik Imputasi Pada Metode C4-5 Untuk Prediksi Penyakit Ginjal KroniS*. *8*(1).

Karno, A. S. B., Hastomo, W., Arif, D., Moreta, E. S., Gunadarma, U., No, J. M. R., & Barat, J. (2020). *Optimasi Portofolio Dan Prediksi Cryptocurrency Menggunakandeep Learning Dalam Bahasa Python*. *4*.

Karyadi, Y. (2022). Prediksi Kualitas Udara Dengan Metoda LSTM, Bidirectional LSTM, dan GRU. *JATISI (Jurnal Teknik Informatika dan Sistem Informasi)*, *9*(1), 671–684. https://doi.org/10.35957/jatisi.v9i1.1588

Khalis Sofi, Aswan Supriyadi Sunge, Sasmitoh Rahmad Riady, & Antika Zahrotul Kamalia. (2021). Perbandingan Algoritma Linear Regression, Lstm, Dan Gru Dalam Memprediksi Harga Saham Dengan Model Time Series. *Seminastika*, *3*(1), 39–46. https://doi.org/10.47002/seminastika.v3i1.275

Liu, Q., Tao, Z., Tse, Y., & Wang, C. (2022). Stock market prediction with deep learning: The case of China. *Finance Research Letters*, *46*, 102209. https://doi.org/10.1016/j.frl.2021.102209

Maghriby, M. A., & Irawan, H. (2023). Analisis Persepsi Publik Mengenai Resesi Ekonomi Global 2023 Sektor Bisnis di Media Sosial Twitter Menggunakan Algoritma Naïve Bayes dan Topic Modelling. *Widya Cipta: Jurnal Sekretari Dan Manajemen*, *7*(2), 74–85. https://doi.org/10.31294/widyacipta.v7i2.15577

Maulana, A., Martanto, M., & Ali, I. (2024). Prediksi Hasil Produksi Panen Bawang Merah

Menggunakan Metode Regresi Linier Sederhana. *JATI (Jurnal Mahasiswa Teknik Informatika)*, *7*(4), 2884–2888. https://doi.org/10.36040/jati.v7i4.7281

Meriani, A. P., & Rahmatulloh, A. (2024). Perbandingan Gated Recurrent Unit (Gru) Dan Algoritma Long Short Term Memory (Lstm) Linear Refression Dalam Prediksi Harga Emas Menggunakan Model Time Series. *Jurnal Informatika dan Teknik Elektro Terapan*, 12(1). https://doi.org/10.23960/jitet.v12i1.3808

Nabillah, I., & Ranggadara, I. (2020). Mean Absolute Percentage Error untuk Evaluasi Hasil Prediksi Komoditas Laut. *JOINS (Journal of Information System)*, *5*(2), 250–255. https://doi.org/10.33633/joins.v5i2.3900

Niederhoffer, V., & Regan, P. J. (2018). Earnings Changes, Analysts' Forecasts and Stock Prices. *Financial Analysts Journal*, *28*(3), 65–71. https://doi.org/10.2469/faj.v28.n3.65

Nilsen, A. (2022). Perbandingan Model RNN, Model LSTM, dan Model GRU dalam Memprediksi Harga Saham-Saham LQ45. *Jurnal Statistika dan Aplikasinya*, 6(1), 137–147. https://doi.org/10.21009/JSA.06113

Nirad, D. W. S., & Surendro, K. (2018). Analisis Data Tracer Study Dengan Mengidentifikasi Outlier Menggunakan Teknik Data Mining. *Jurnal Momentum*, *20*.

Nugroho, P. A., Fenriana, I., Arijanto, R., & Kom, M. (2020). *Learning Menggunakan Convolutional Neural Network (Cnn) Pada Ekspresi Manusia*. *2*(1).

Permana, A. H., Pohan, E. R., & Ananda, Y. Y. (2022). Mengukur Pengaruh CAR, ROA, NIM, LDR, dan Rasio NPL terhadap Harga Saham Bank pada Era Pre-Pandemic dan Era During Pandemic Covid-19. *Syntax Idea*, *4*(2), 281–300. https://doi.org/10.46799/syntax-idea.v4i2.1768

Phan, D. H. B., & Narayan, P. K. (2020). Country Responses and the Reaction of the Stock Market to COVID-19—A Preliminary Exposition. *Emerging Markets Finance and Trade*, *56*(10), 2138–2150. https://doi.org/10.1080/1540496X.2020.1784719

Pradana, D. B. P. (2017). *Pengaruh Penerapan Tools Google Classroom Pada Model Pembelajaran Project Based Learning Terhadap Hasil Belajar Siswa*. *02*.

Pratama, A. R. I., Latipah, S. A., & Sari, B. N. (2022). Optimasi Klasifikasi Curah Hujan Menggunakan Support Vector Machine (Svm) Dan Recursive Feature Elimination (Rfe). *JIPI (Jurnal Ilmiah Penelitian Dan Pembelajaran Informatika)*, *7*(2), 314–324. https://doi.org/10.29100/jipi.v7i2.2675

Prayogi, A. (2021). Rasio Pasar sebagai Faktor Prediktif dalam Pengembalian Investasi. *Journal of Economic, Management, Accounting and Technology*, *4*(2), 149–159. https://doi.org/10.32500/jematech.v4i2.1669

Rasyid, Dewi Agushinta R., & Dharma Tintri Ediraras. (2021). Deep Learning Methods In Predicting Indonesia Composite Stock Price Index (IHSG). *International Journal of Computer and Information Technology(2279-0764)*, *10*(5). https://doi.org/10.24203/ijcit.v10i5.153

Rizvi, S. A. R., Juhro, S. M., & Narayan, P. K. (2021). Understanding market reaction to COVID-19 monetary and fiscal stimulus in major ASEAN countries. *Buletin Ekonomi Moneter Dan Perbankan*, *24*(3), 313–334. https://doi.org/10.21098/bemp.v24i3.1690

Robinson, R. S. (2022). Purposive Sampling. In A. C. Michalos (Ed.), *Encyclopedia of Quality of Life and Well-Being Research* (1st ed., pp. 5243–5245). Springer Netherlands. https://doi.org/10.1007/978-94-007-0753-5_2337

Sethia, A., & Raut, P. (2019). Application of LSTM, GRU and ICA for Stock Price Prediction. In S. C. Satapathy & A. Joshi (Eds.), *Information and Communication Technology for Intelligent Systems* (Vol. 107, pp. 479–487). Springer Singapore. https://doi.org/10.1007/978-981-13-1747-7_46

Sihombing, P. R., Suryadiningrat, S., Sunarjo, D. A., & Yuda, Y. P. A. C. (2023). Identifikasi Data Outlier (Pencilan) dan Kenormalan Data Pada Data Univariat serta Alternatif Penyelesaiannya. *Jurnal Ekonomi Dan Statistik Indonesia*, *2*(3), 307–316. https://doi.org/10.11594/jesi.02.03.07

Siringoringo, R., Angin, R. P., Rumahorbo, B., & No, J. H. T. (2022). *Model Klasifikasi Genetic-Xgboost Dengan T-Distributed Stochastic Neighbor Embedding Pada Peramalan Pasar*. *1*.

Sonkavde, G., Dharrao, D. S., Bongale, A. M., Deokate, S. T., Doreswamy, D., & Bhat, S. K. (2023). Forecasting Stock Market Prices Using Machine Learning and Deep Learning Models: A Systematic Review, Performance Analysis and Discussion of Implications. *International Journal of Financial Studies*, *11*(3), 94. https://doi.org/10.3390/ijfs11030094

Suryanegara, G. A. B., & Purbolaksono, M. D. (2021). *Peningkatan Hasil Klasifikasi pada Algoritma Random Forest untuk Deteksi Pasien Penderita Diabetes Menggunakan Metode Normalisasi*. *5*(1).

Suzuki, M., Sakaji, H., Izumi, K., & Ishikawa, Y. (2022). Forecasting Stock Price Trends by Analyzing Economic Reports With Analyst Profiles. *Frontiers in Artificial Intelligence*, *5*, 866723. https://doi.org/10.3389/frai.2022.866723

Syahfitri, N., Rahmadani, N., & Nasution, N. S. (2023). *Penggunaan Metode Statistik Deskriptif dalam Menganalisis Hasil pemilu*. *2*(1).

Widiputra, H., & Juwono, E. (2024). Parallel multivariate deep learning models for time-series prediction: A comparative analysis in Asian stock markets. *IAES International Journal of Artificial Intelligence (IJ-AI)*, *13*(1), 475. https://doi.org/10.11591/ijai.v13.i1.pp475-486

Wilsen, W., Rahayu, W., & Santi, V. M. (2018). Penerapan Imputasi Ganda dengan Metode Predictive Mean Matching (PMM) untuk Pendugaan Data Hilang pada Model Regresi Linear. *Jurnal Statistika dan Aplikasinya*, *2*(1), 12–20. https://doi.org/10.21009/JSA.02102

Yahaya, O. (2021). Analysts' forecasts and stock prices: Evidence from Nigeria. *Iranian Journal of Accounting, Auditing and Finance*, *Online First*. https://doi.org/10.22067/ijaaf.2021.40230