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APPLICATION OF ARTIFICIAL NEURAL NETWORK METHOD USING HYPERPARAMETER TUNING FOR PREDICTION OF EURO EXCHANGE RUPIAH

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Abstrak

The Covid-19 pandemic has significantly impacted the economic decline in many countries, such as Italy, the United States and the European Union. Indonesia, also affected by Covid-19, was not spared from economic turmoil, especially in the foreign exchange market, where the rupiah exchange rate against the Euro experienced significant fluctuations in early 2020, hampering international trade and investment activities. Therefore, an appropriate method is needed to predict changes in the rupiah exchange rate against the Euro to minimize the obstacles. This study uses the ANN model to predict the Rupiah (Rp) exchange rate against the Euro (€). The best model is obtained through the hyper-tuning process. The optimal parameter values obtained are the input layer with 10 nodes, 2 hidden layers with 19 nodes and 13 nodes, the output layer, dropout of 0.2, 32 batch sizes, 100 epochs, and the Tanh activation function in the distribution scheme of 90% training data and 10 % testing data. Based on the MAPE value of 0.0042% and 0.0041% obtained, the prediction results on the selling and buying rates of the Rupiah against the Euro, it can be concluded that the model has good predictive ability with an accuracy value of 99.996%.

Keywords: *Currency Exchange Rates, Data Mining, Machine Learning, Artificial Neural Networks*

1. INTRODUCTION

The spread of the Covid-19 pandemic has resulted in a global economic downturn of 1%, impacting the economies of many countries such as China, Italy, the United States and the European Union. Also affected by Covid-19, Indonesia was not spared from economic turmoil [1], especially in the foreign exchange market, where the rupiah exchange rate against the Euro experienced significant fluctuations in early 2020. This increase in volatility became one of the obstacles that affected trading activities and international investment both directly and indirectly [2]. Therefore, an appropriate method is needed to predict changes in the rupiah exchange rate against the Euro to minimize the obstacles.

Prediction methods usually only use classical statistical models to get accurate results [3], such as Auto-regressive (AR), Moving Average (MA), Auto-regressive Integrated Moving Average (ARIMA), and Seasonal Auto-regressive Integrated Moving Average (SARIMA) [4]. However, this method requires several assumptions that must be met, and the ARIMA model can only be used for linear data [5]. Therefore, the ARIMA method is complicated to use to predict data that contains fluctuations such as foreign currency exchange rates. Then, along with the rapid development of computer technology and the increasingly widespread use of Artificial Intelligence (AI), researchers and practitioners turn to Artificial Neural Networks (ANN) as an alternative method for predictions based on time series data.

Artificial Neural Network (ANN), or Neural Network, is a computational method that can process information to handle tasks such as regression, classification and prediction. Artificial Neural Network is part of AI inspired by the human brain and artificial nervous system [6]. The ANN architecture generally consists of three layers: the input, hidden, and output layers [7].

Related research that applies the ANN model for predictions, including by Kakar et al. [8], aims to predict and classify weather based on humidity, speed, and other factors. Researchers increase the number of hidden layers in their model. The results show that the ANN model can predict and classify weather variables with a lower error rate.

Lau et al. [9] identified factors that could affect student performance using ANN. Furthermore, the ANN model is evaluated with metrics such as Mean Square Error (MSE) and confusion matrix. Overall, the ANN model can be considered an excellent predictive model with an accuracy rate of 84.8%.

Furthermore, Alsulaili and Refaie [10] utilized the ANN model to save time in measuring BOD5 in wastewater. This study explores the use of ANN in predicting influent BOD5 concentrations and WWTP performance, which includes COD, BOD, and TSS concentrations in effluent. The research findings show that the ANN model performs well, achieving significant R2 values of 0.752, 0.612, 0.631, and 0.754 for predicting BOD, COD, TSS, and BOD5.

In 2022, Rashid et al. [11] proposed an AI approach using the ANN and Particle Swarm Optimization (PSO) methods to predict five common chronic diseases, including breast cancer, diabetes, heart attack, hepatitis, and kidney disease. The ANN prediction model built using the PSO-based feature extraction approach is superior to other sophisticated classification approaches in accuracy. The proposed approach provides the highest accuracy of 99.67% using PSO. In addition, optimized ANN processing requires less time than methods based on random forest (RF), deep learning, and support vector machine (SVM).

Alifiah et al. [12] developed an ANN model to predict confirmed cases, recovered cases, and deaths from COVID-19 in Lampung Province from 2021 to 2022 using the k-fold cross-validation procedure to evaluate predictive model performance. From the analysis results, confirmed, recovered, and death cases have decreased, with accuracy rates reaching 98.22%, 98.08% and 99.05%.

Based on various related studies, it can be concluded that ANN has a high level of accuracy. However, optimal ANN training is required for accurate results [13]. Therefore, we propose an ANN model for predicting the rupiah exchange rate against the Euro based on several optimal parameters obtained from the hyper tuning process by comparing the Sigmoid, ReLU, and Tanh activation functions.

2. RESEARCH METHOD

2.1. Dataset

The data used is secondary data obtained from the website https://www.bi.go.id/id/statistik/informasi-kurs/transaksi-bi/. This data contains the exchange rates of the Indonesian Rupiah (Rp) and European Euro (€) for 18 months, from January 2020 to June 2021. Except for weekends and public holidays, this data is recorded daily and consists of 377. The research data used are as follows:

Table 1. Rupiah exchange rate data Rupiah against Euro

Date	Selling Rate	Buying Rate
02/01/2020	15672,34	15510,86
03/01/2020	15615,39	15454,48
…	…	…
29/06/2021	17370,33	17194,61
30/06/2021	17343,78	17165,43

2.2. METHOD

2.2.1. Pre-processing

The initial stage in building a prediction model is data pre-processing, including eliminating duplicate data, examining inconsistent data, and missing values [14]. However, before pre-processing the data, the visualization should be done first to see how the graph of the movement of the rupiah exchange rate against the Euro.

The second stage is data transformation. Data transformation is the process of changing the measurement scale from its original form to a different form to prevent outliers. Several methods transform data, including min-max normalization, standard normalization, and decimal scale.

This study chose standard normalization as the normalization approach concerning the mean value and standard deviation [15]. The equation used for standard normalization is as follows:

$$Z = \frac{x-\mu}{\sigma} \tag{1}$$

2.2.2. Splitting Data

Selanjutnya, dataset yang digunakan dapat dibagi menjadi dua bagian, dengan skema yang berbeda seperti 70:30, 80:20, dan 90:10 train /test split [16]. Train data digunakan untuk membangun model, sedangkan test data digunakan untuk mengevaluasi kemampuan prediksi model.

Splitting data is an essential step in eliminating or reducing bias in the training data during the learning process. The purpose of splitting data is to prevent overfitting [17].

2.2.3. Training Model

The ANN model built to predict the rupiah exchange rate against the Euro in this study will be optimized through a hyperparameter tuning process. Hyperparameters refer to parameters in the model that have been determined before the training process begins [12]. By finding the optimal combination of parameters, the model can work well. Therefore, we use a hyper-tuning technique. The hyper-tuning process is carried out with early stopping so that the model's learning process stops when the conditions

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are met [18]. Some of the hyperparameters we optimize in this study are the number of nodes in the hidden layer, dropout, epoch, and batch size.

a. Nodes on Hidden Layer

The success of ANN training depends on determining the appropriate number of nodes in the hidden layer [19] to prevent underfitting or overfitting. In most cases, there is no definite method to determine the optimal number of neurons without training the network [20]. Therefore, we try to apply hyper-tuning to these parameters.

b. Dropout

Dropout is used to overcome overfitting [21] by regulating the neural network, namely removing nodes randomly in a layer with a certain probability (rate) during training without modifying the loss function. The optimal dropout is usually between 0.2 and 0.5, meaning about 20% to 50% of neurons are randomly dropped in the network. However, too many disconnections of neurons can cause an imbalance in the network and not achieve the desired output.

c. Epoch dan Batch Size

An epoch is a recurring period during the network training process, during which input is given, and the network weights are updated [22]. Meanwhile, batch size refers to the amount of training used in one iteration and is one of the most critical hyperparameters [23].

In addition, we compared several activation functions often used in ANNs, such as ReLU, Sigmoid, and Tanh [24], to determine the most efficient computational model [25].

a. Rectified Linear Unit (ReLU)

ReLU is an activation function used to normalize the value generated by the layer. The mathematical equation for this activation function is:

$$f(x) = \max(0, x) \tag{2}$$

b. Sigmoid

The sigmoid function is often used as an activation function in ANN. This function returns a value between 0 and 1. The sigmoid function has the following equation:

$$f(x) = \frac{1}{1+e^{-x}} \tag{3}$$

c. Tanh

The Tanh activation function is an alternative to the sigmoid activation function. Although both are "S" shaped, the Tanh function returns values between -1 and 1. Therefore, although similar to the sigmoid function, its wider range of values makes it more effective in complex nonlinear modelling. The Tanh function has the following equation:

$$f(x) = \frac{e^{x}-e^{-x}}{e^{x}+e^{-x}} \tag{4}$$

2.2.4. Model Evaluation

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Model evaluation is an important stage in making predictions, which aims to measure the suitability between actual and predicted data [26]. Several indicators that can be used to evaluate the model include Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE) [27].

a. Mean Absolute Percentage Error

Mean Absolute Percentage Error (MAPE) is a metric that calculates the percentage difference between the predicted value and the actual value.

b. Mean Squared Error dan Root Mean Squared Error

Mean Squared Error (MSE) and Root Mean Squared Error (RMSE) are measures used to measure the average difference between predicted and actual values, emphasizing more significant errors than more minor errors in evaluating model performance. The ideal value for MSE and RMSE is zero.

MAPE, MSE and RMSE mathematical equations are as follows:

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - X_i}{Y_i}\right| \quad (5)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(X_i - Y_i)^2 \quad (6)$$

$$RMSE = \sqrt{MSE} \quad (7)$$

where:

X_i = predicted i-th value
Y_i = i-th actual value
n = number of trials

3. RESULTS AND ANALYSIS

3.1. Data Input

First, input the exchange rate data between the Rupiah and the Euro, which consists of two variables: the buying and selling rates, into the Python software. This data covers the period from January 1, 2020, to June 30, 2021, for 377 data.

3.2. Data Visualization

The data that has been input is then processed into a time series format and visualized in the form of a plot to observe the movement of the data and the type of plot that is produced

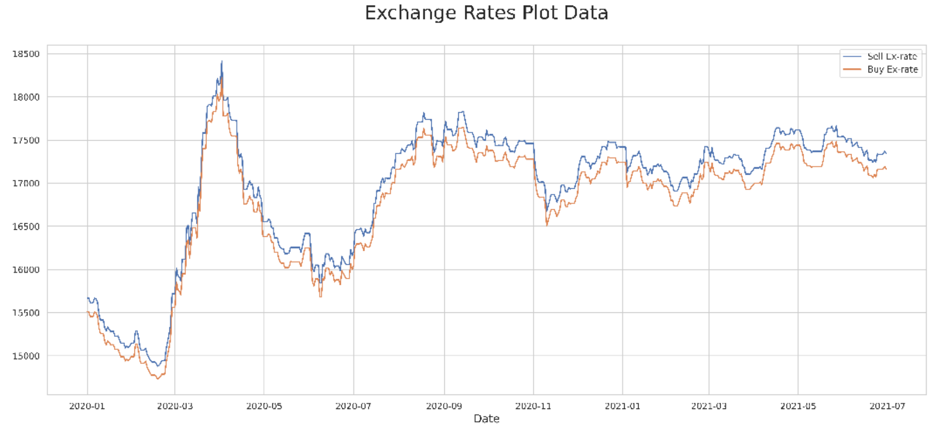

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Figure 1. Data Plot of Selling and Buying Exchange Rate of Rupiah against Euro

Based on Figure 2, it can be concluded that the graph of the buying and selling rates of the Rupiah against the Euro shows a trend data pattern, where there are fluctuations up and down in the data.

3.3. Pre-processing Data

Before building the ANN model, the first step that must be done is data pre-processing, which includes checking for missing values, outliers, and scaling data. During checking for missing values, no missing values were found. However, when checking for outliers, it is detected that some data is outside the range of expected values. Therefore, it is necessary to transform the data using standard normalization to overcome the presence of outliers.

3.4. Splitting Data

The next stage is to divide the data into 2 parts, namely training data and testing data, as shown in the table below:

Table 1. Splitting into Training Data and Testing Data

Splitting Data	***Training***	***Testing***
70% and 30%	382	165
80% and 20%	437	110
90% and 10%	492	55

3.5. Building Model *Artificial Neural Network*

This study built an ANN model with the following architecture: an input layer, 2 hidden layers, an output layer, and an activation function Sigmoid, ReLU, Tanh. In addition, several hyper tuning parameters are also used to improve the model's performance, including:

1. Nodes in hidden layer : 7, 13, 19
2. Dropout : 0.2, 0.3
3. Epoch : 50, 100
4. Batch size : 16, 32

Based on the hyper-tuning process, the best parameters are obtained as follows:

Table 2. Parameters used in the Artificial Neural Network model
(70% training & 30% testing scheme)

Parameter	Sigmoid		ReLU		Tanh	
	Selling Rate	Buying Rate	Selling Rate	Buying Rate	Selling Rate	Buying Rate

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Batch Size	16	16	16	32	16	16
Epoch	100	50	100	100	100	100
Dropout	0.3	0.2	0.2	0.2	0.2	0.2
Input Layer (nodes)	1 layer (10)	1 layer (10)	1 layer (10)	1 layer (10)	1 layer (10)	1 layer (10)
Hidden layer (nodes)	2 layer (19, 13)	2 layer (19, 7)	2 layer (13, 13)	2 layer (19, 13)	2 layer (19, 13)	2 layer (19, 13)
Output Layer	1 layer	1 layer	1 layer	1 layer	1 layer	1 layer

Table 3. Parameters used in the Artificial Neural Network model
(80% training & 20% testing scheme)

Parameter	Sigmoid		ReLU		Tanh	
	Selling Rate	Buying Rate	Selling Rate	Buying Rate	Selling Rate	Buying Rate
Batch Size	16	16	16	32	16	16
Epoch	100	50	100	100	100	100
Dropout	0.3	0.2	0.2	0.2	0.2	0.2
Input Layer (nodes)	1 layer (10)	1 layer (10)	1 layer (10)	1 layer (10)	1 layer (10)	1 layer (10)
Hidden layer (nodes)	2 layer (19, 13)	2 layer (19, 7)	2 layer (13, 13)	2 layer (19, 13)	2 layer (19, 13)	2 layer (19, 13)
Output Layer	1 layer	1 layer	1 layer	1 layer	1 layer	1 layer

Table 4. Parameters used in the Artificial Neural Network model
(90% training & 10% testing scheme)

Parameter	Sigmoid		ReLU		Tanh	
	Selling Rate	Buying Rate	Selling Rate	Buying Rate	Selling Rate	Buying Rate
Batch Size	32	16	32	32	32	32
Epoch	100	50	100	100	100	100
Dropout	0.2	0.2	0.2	0.2	0.2	0.2
Input Layer (nodes)	1 layer (10)	1 layer (10)	1 layer (10)	1 layer (10)	1 layer (10)	1 layer (10)
Hidden layer (nodes)	2 layer (19, 13)	2 layer (19, 7)	2 layer (19, 13)	2 layer (19, 13)	2 layer (19, 13)	2 layer (19, 13)
Output Layer	1 layer	1 layer	1 layer	1 layer	1 layer	1 layer

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3.6. Model Evaluation

After obtaining the best model, the next step is to visualize the loss value and validate the loss value to show the effectiveness of the model. This model uses MSE as a loss function.

The figure below is a model testing plot using a 70% training and 30% testing scheme.

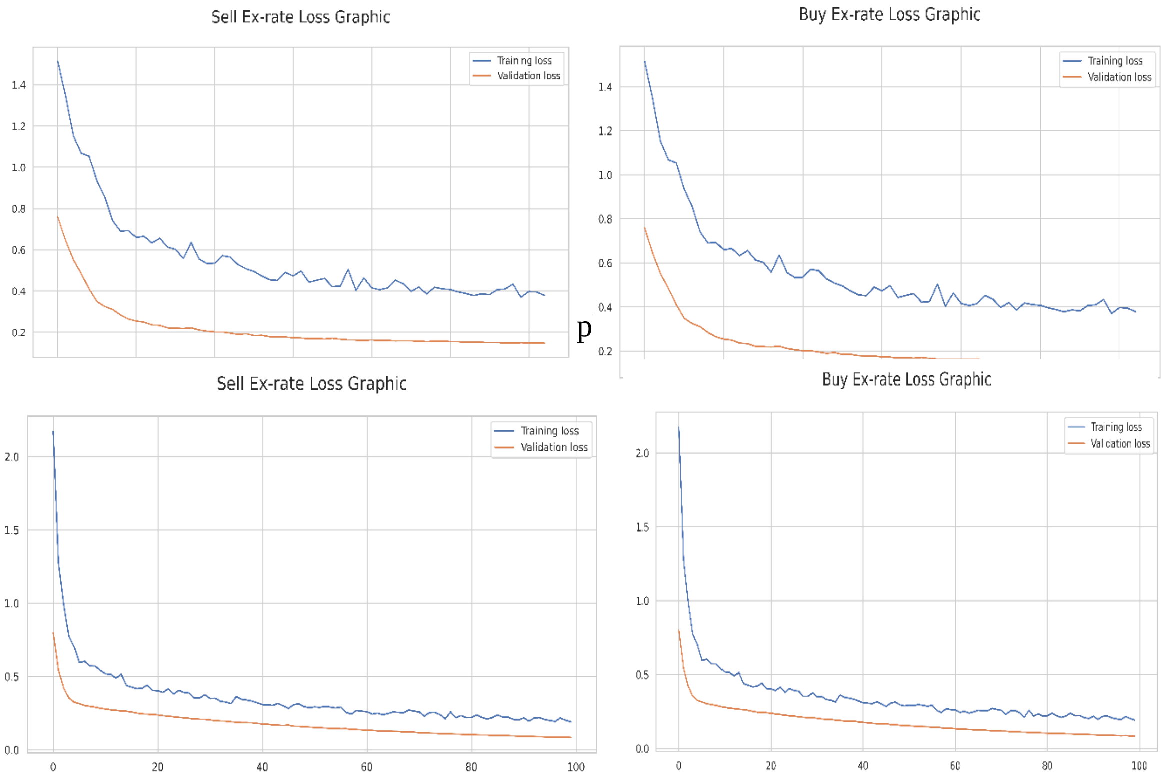

Figure 3. Loss Graph with ReLU Function

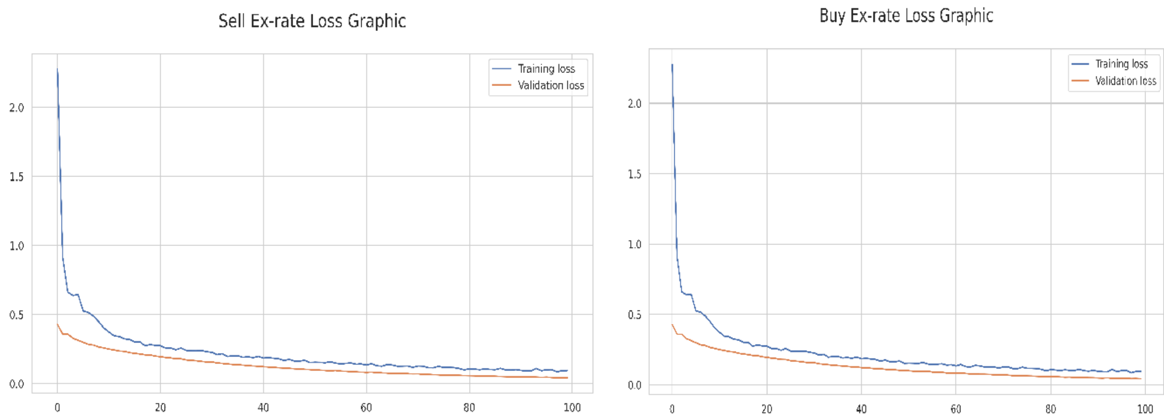

Figure 4. Loss Graph with Tanh Function

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The graph below is a model testing plot with a scheme of 80% training and 20% testing.

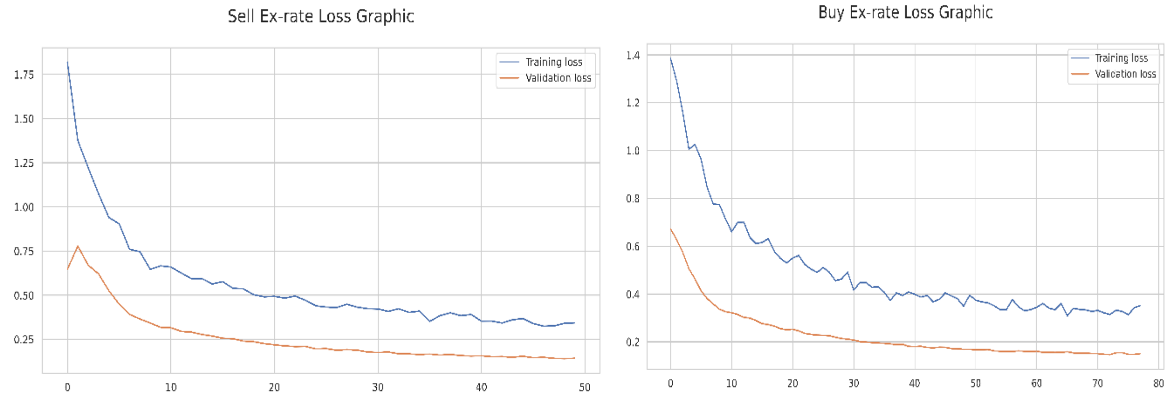

Figure 5. Loss Graph with Sigmoid Function

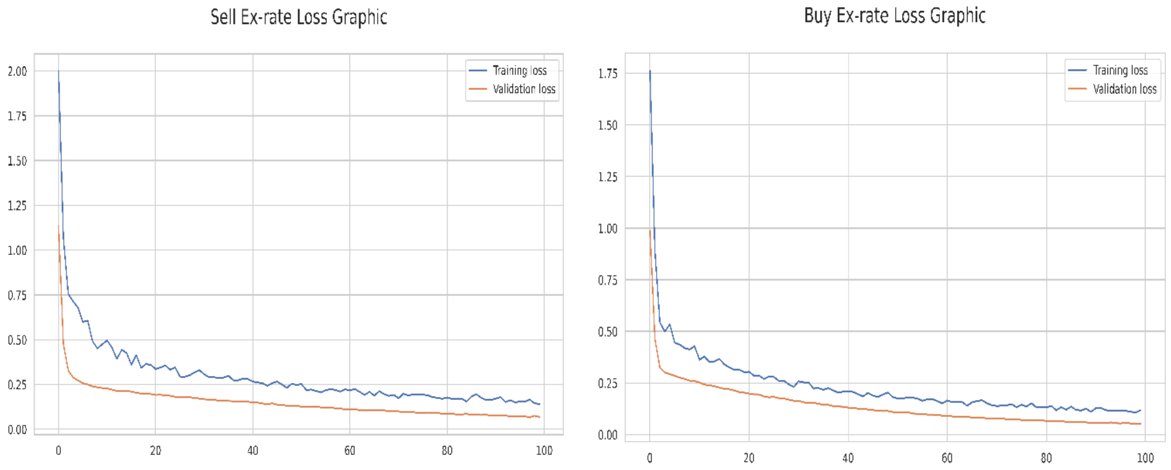

Figure 6. Loss Graph with ReLU Function

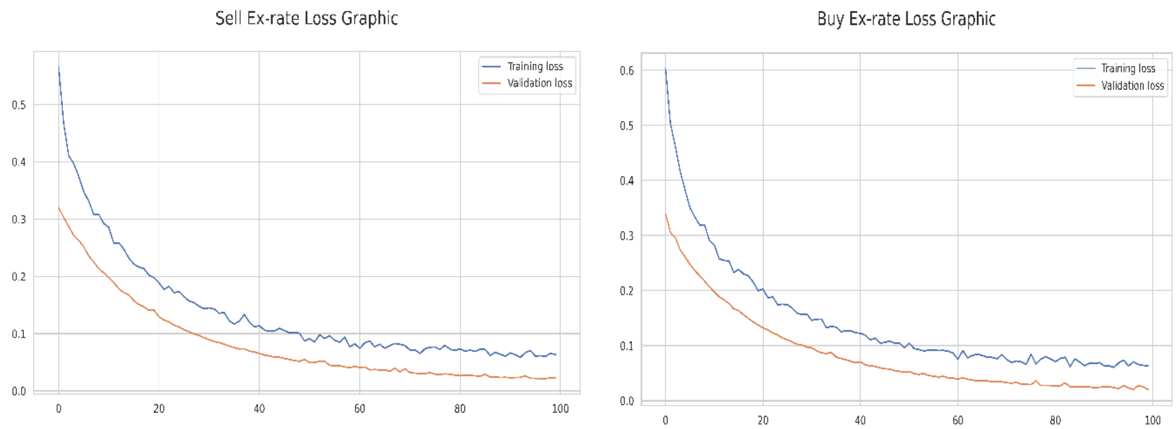

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Figure 7. Loss Graph with Tanh Function

Furthermore, the graph below is a model testing plot with a 90% training and 10% testing scheme.

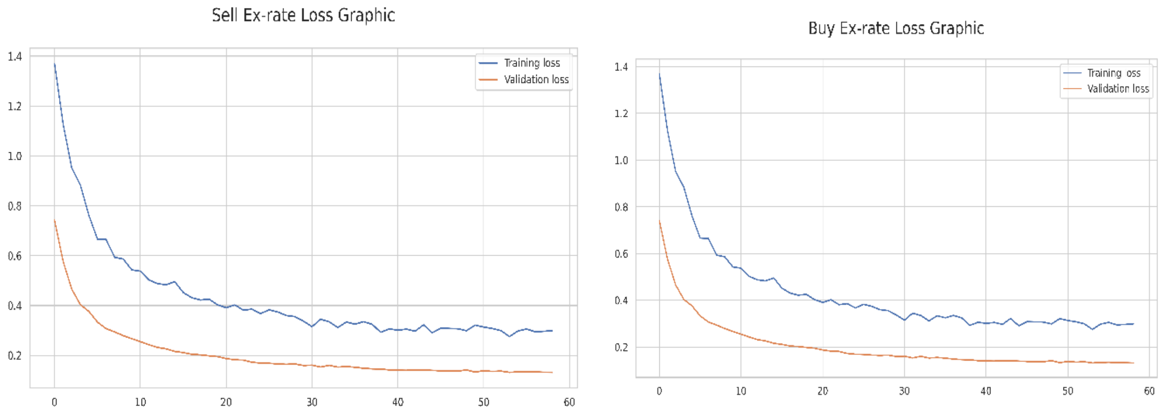

Figure 8. Loss Graph with Sigmoid Function

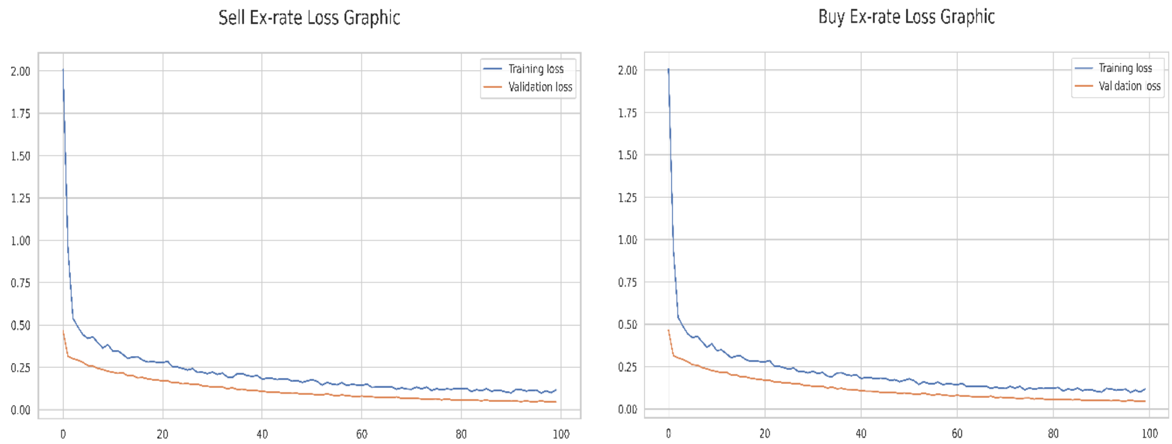

Figure 9. Loss Graph with ReLU Function

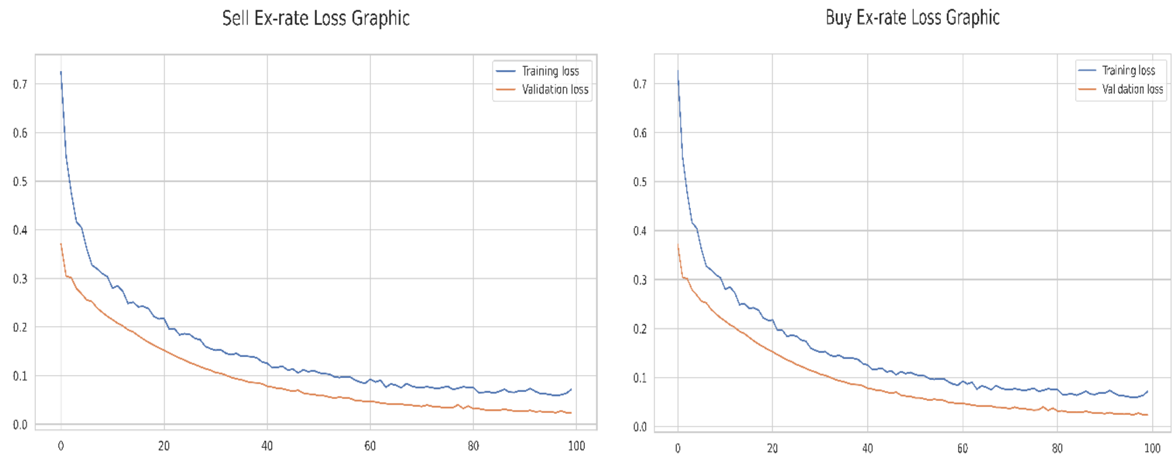

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Figure 10. Loss Graph with Tanh Function

Based on Figure 2-10, the loss graph with the Sigmoid activation function is not optimal because the difference in loss and validation loss values is quite significant. Meanwhile, the loss graph with the ReLU and Tanh activation functions shows a more optimal model because there is no significant difference between loss and validation loss.

3.7. Prediction

Predicted data obtained from the ANN model using the best parameters will be compared with the actual data after denormalization to return previously normalized data to its original value. If the prediction results are close to actual data, then the model can be used to predict the selling and buying rates of the Rupiah against the Euro in the future.

The graph below plots the predicted results with a schematic of 70% training data and 30% testing data.

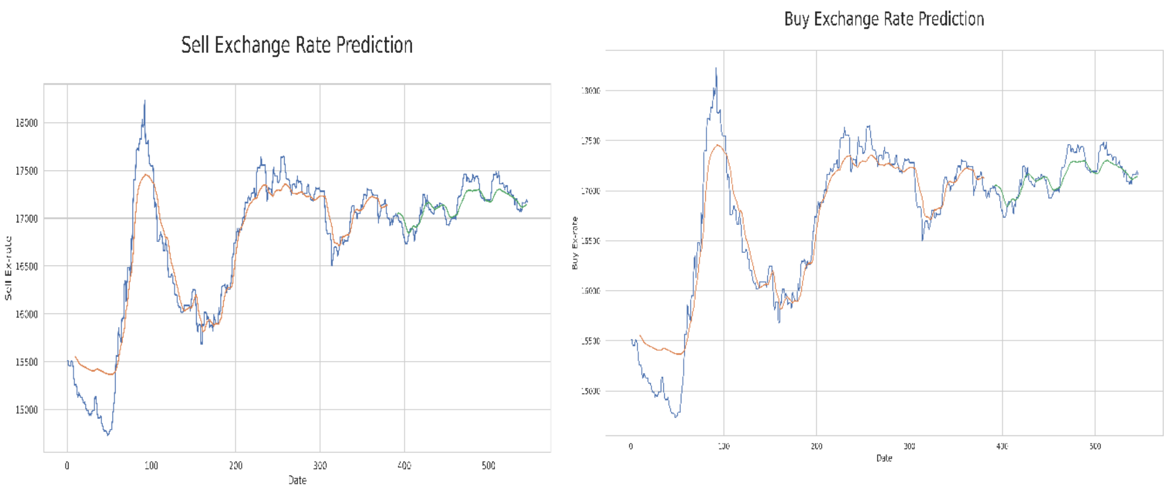

Figure 11. Comparison of Actual and Predicted Data with the Sigmoid Function

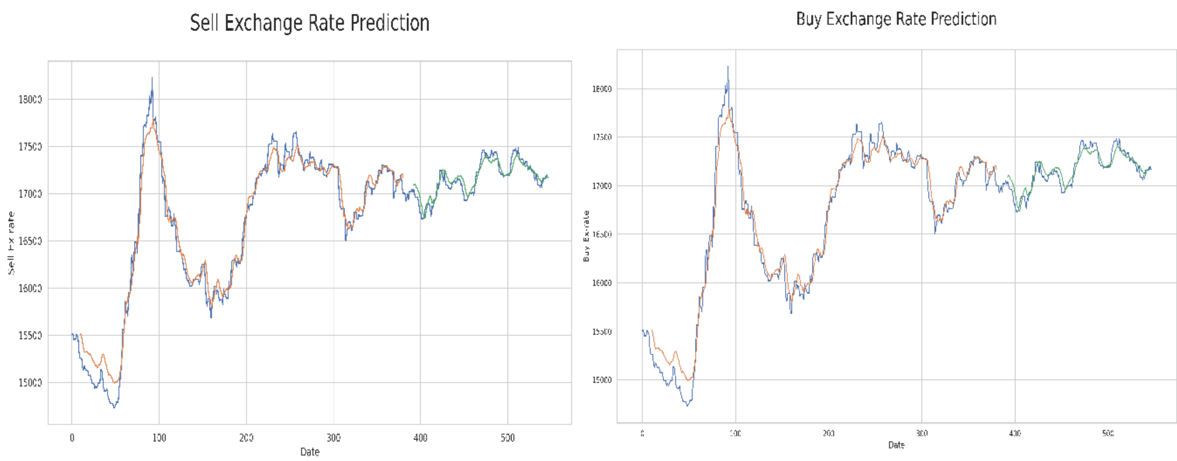

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Figure 12. Comparison of Actual and Predicted Data with the ReLU Function

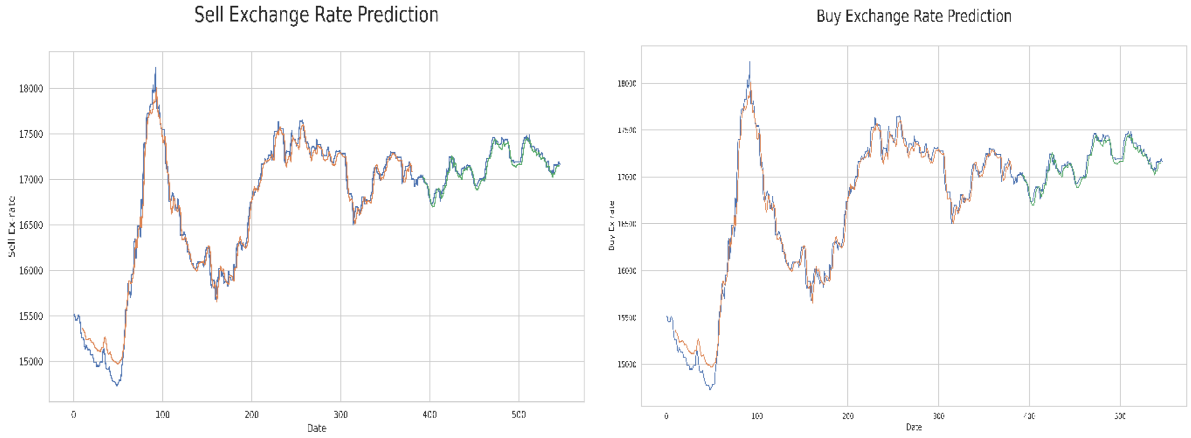

Figure 13. Comparison of Actual and Predicted Data with the Tanh Function

The graph below is a predicted result with a scheme of 80% training and 20% testing.

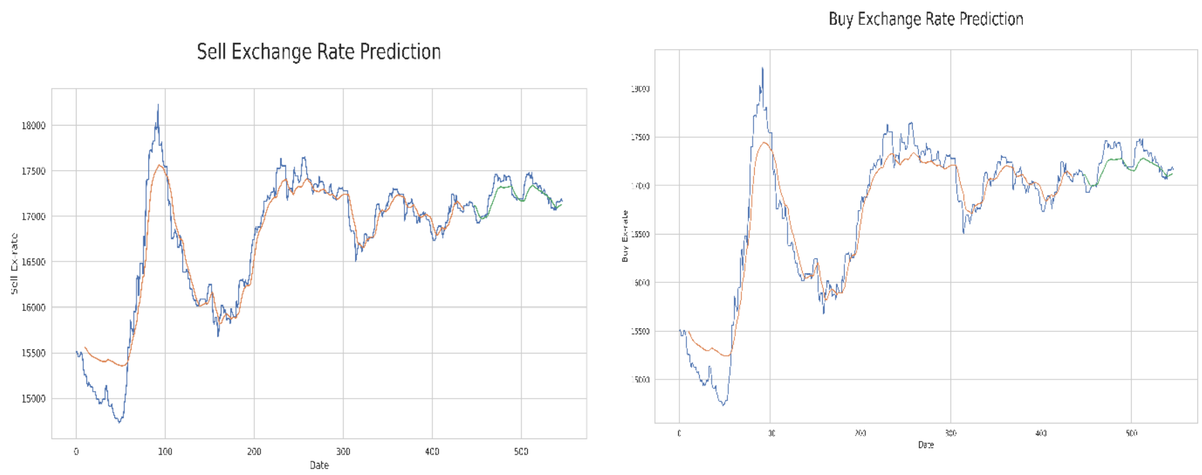

Figure 14. Comparison of Actual and Predicted Data with the Sigmoid Function

Figure 16. Comparison of Actual and Predicted Data with the Tanh Function

Furthermore, the graph below is a predicted result with a schematic of 90% training and 10% testing data.

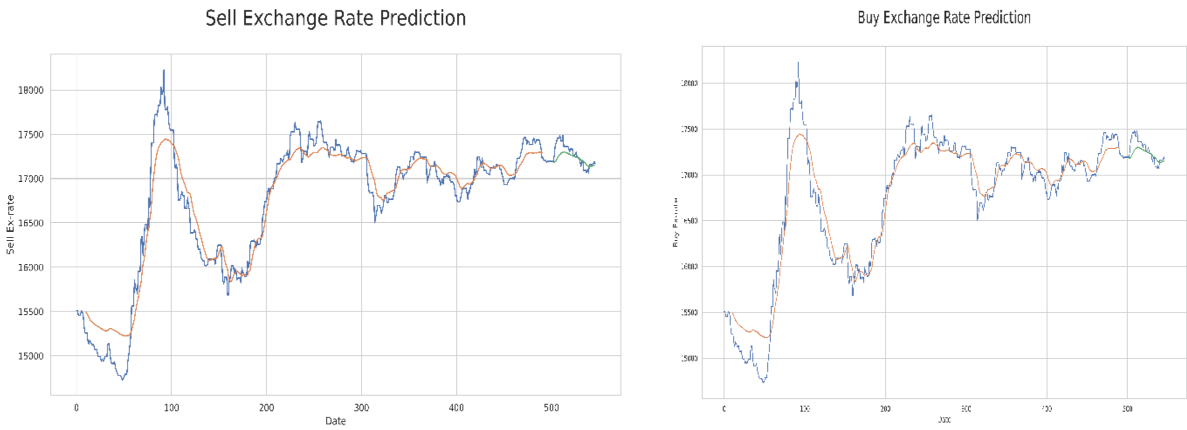

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Figure 17. Comparison of Actual and Predicted Data with the Sigmoid Function

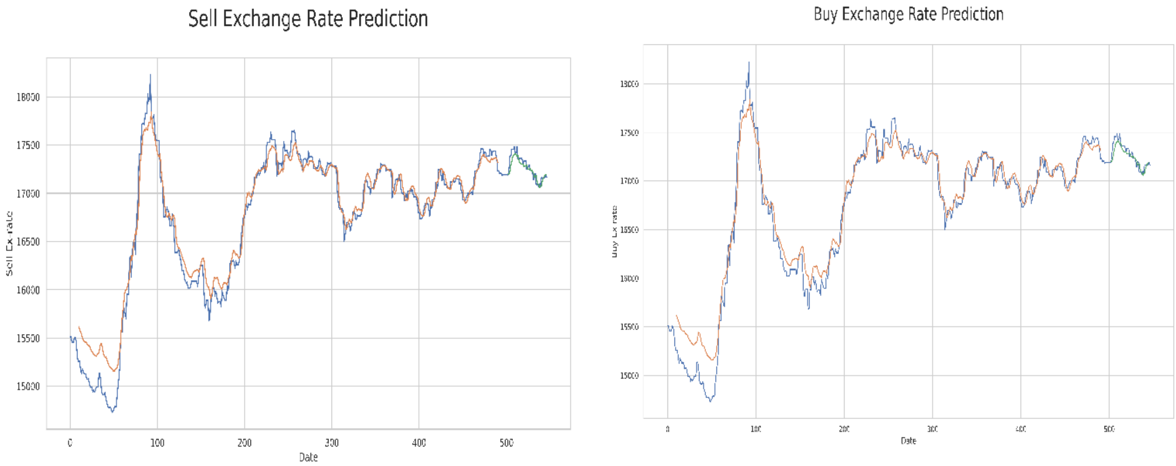

Figure 18. Comparison of Actual and Predicted Data with the ReLU Function

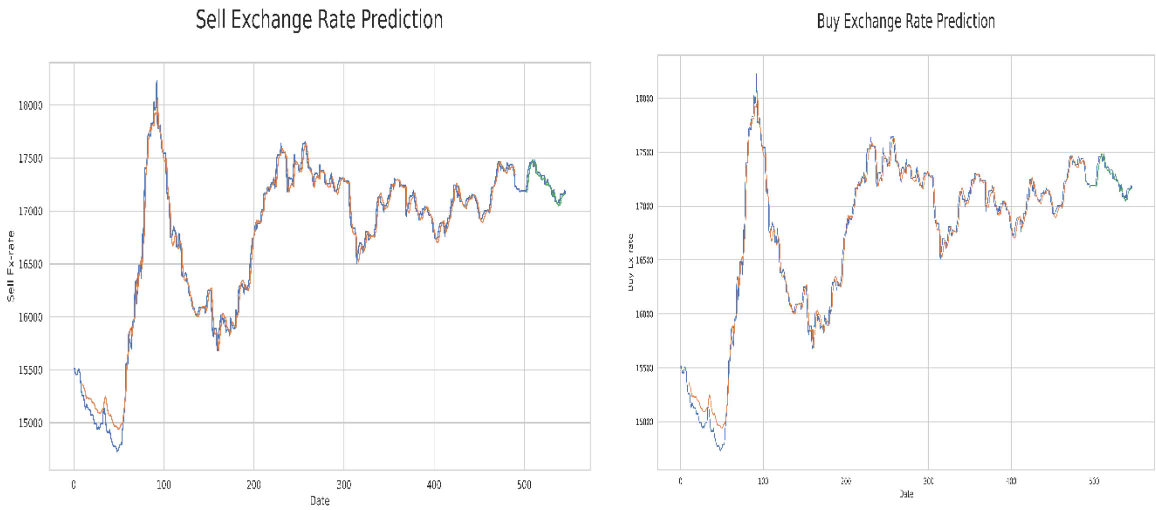

Figure 19. Comparison of Actual and Predicted Data with the Tanh Function

Based on Figures 11-19, the plot of the predicted results using the Sigmoid activation function is slightly away from the actual data distribution pattern. That shows a slight difference between the predicted results and the actual data, but the model built is still quite good. On the other hand, the plot of the predicted results using the ReLU and Tanh activation functions follows the actual data distribution pattern well. There is no significant difference between the predicted results and the actual data, so it can be said that the model built is good.

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3.8. Comparison of ANN Model Evaluation Metrics

The prediction results will be evaluated using the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). That aims to evaluate the performance and accuracy of the model that has been built.

Table 5. Model Evaluation of the ANN with Scheme 70% training & 30% testing.

Evaluation Metrics	*Sigmoid*		*ReLU*		*Tanh*	
	Selling Rate	Buying Rate	Selling Rate	Buying Rate	Selling Rate	Buying Rate
RMSE	0.122	0.140	0.093	0.093	0.075	0.075
MAPE	0.0099%	0.011%	0.0063%	0.0063%	0.0050%	0.0050%
Accuracy	99.990%	99.988%	99.993%	99.993%	99.995%	99.995%

Table 6. Model Evaluation of the ANN with Scheme 80% *training* & 20% *testing.*

Evaluation Metrics	*Sigmoid*		*ReLU*		*Tanh*	
	Selling Rate	Buying Rate	Selling Rate	Buying Rate	Selling Rate	Buying Rate
RMSE	0.180	0.158	0.088	0.072	0.079	0.061
MAPE	0.0112%	0.0096%	0.0078%	0.0064%	0.0050%	0.0042%
Accuracy	99.988%	99.990%	99.992%	99.993%	99.995%	99.996%

Table 7. Model Evaluation of the ANN with Scheme 90% *training* & 10% *testing.*

Evaluation Metrics	*Sigmoid*		*ReLU*		*Tanh*	
	Selling Rate	Buying Rate	Selling Rate	Buying Rate	Selling Rate	Buying Rate
RMSE	0.126	0.140	0.072	0.072	0.065	0.064
MAPE	0.0093%	0.0097%	0.0068%	0.0068%	0.0042%	0.0041%
Accuracy	99.990%	99.990%	99.993%	99.993%	99.996%	99.996%

As shown in Tables 5, 6, and 7, the ANN model for buying and selling rates shows the best results when using the Tanh activation function and the 90% training scheme: 10% testing with MAPE values of 0.0042% and 0.0041%. Thus, it can be interpreted that the results show outstanding predictive ability with an accuracy rate of up to 99.996% for buying and selling exchange rates.

4. CONCLUSION

This study uses the ANN model to predict the selling and buying exchange rates of the Rupiah against the Euro using data obtained from https://www.bi.go.id/id/statistik/informasi-kurs/transaksi-bi/ starting from January 2020

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to June 2021 with a total of 377 data. In practice, we use data splitting schemes, including 70%:30%, 80%:20%, and 90%:10%, by comparing the 3 activation functions: Sigmoid, ReLU, and Tanh. Meanwhile, hyper tuning is carried out on several parameters to make the model more optimally built, such as the number of nodes in the hidden layer, dropout, batch size, and epoch.

The results show that the best model for predicting the selling and buying rates of the Rupiah against the Euro is with a scheme of 90% training data and 10% testing data, 10 nodes input layer, 2 hidden layers with 19 nodes and 13 nodes, output layer with 1 node, 0.2 dropouts, 32 batch sizes, 100 epochs, and Tanh activation function. This model has good predictive ability with an accuracy of up to 99.996% for the selling and buying rates of the Rupiah against the Euro.

References

[1] I. Moridu, "Impact of Covid-19 on Rupiah Exchange Rate Movement Against Dollars and Composite Stock Price Index in Indonesia," *Journal of Applied Business Administration,* pp. 76-83, 2022.

[2] J. Mehtiyev, R. Magda and L. Vasa, "Exchange Rate Impacts on International Trade," *Economic Annals - XXI,* vol. 190, no. 5-6, pp. 12-22, 2021.

[3] S. M. Shakeel, N. S. Kumar, P. P. Madalli, R. Srinivasaiah and D. R. Swamy, "COVID-19 Prediction Models: a Systematic Literature Review," *Osong Public Health and Research Perspectives,* vol. 12, no. 4, pp. 215-229, 2021.

[4] K. H. Gusti, Irhamah and H. Kuswanto, "Hybrid Double Seasonal ARIMA and Support Vector Regression in Short-Term Electricity Load Forecasting," in *The 6th International Seminar on Science and Technology*, Surabaya, Indonesia, 2020.

[5] G. A. M. A. Putri, N. P. N. Hendayanti and M. Nurhidayati, "Pemodelan Data Deret Waktu dengan Autoregressive Integrated Moving Average dan Logistic Smoothing Transition Autoregressive," *Jurnal Varian,* vol. 1, no. 1, pp. 54-63, 2017.

[6] Y. Tian, M. Shu and Q. Jia, "Artificial Neural Network," in *Encyclopedia of Earth Sciences Series*, Springer, 2022, pp. 1-4.

[7] P. S. Kumar and S. Sivamani, "Numerical Analysis and Implementation of Artificial Neural Network Algorithm for Nonlinear Function," *International Journal of Information Technology,* vol. 13, pp. 2059-2068, 2021.

[8] S. A. Kakar, S. Iqbal, A. Rehman, H. A. Kakar, A. Naseem, B. A. Kakar and B. Khan, "Artificial Neural Network based Weather Prediction using Back Propagation Technique," *(IJACSA) International Journal of Advanced Computer Science and Applications,* vol. 9, no. 8, pp. 462-470, 2018.

[9] E. T. Lau, L. Sun and Q. Yang, "Modelling, Prediction and Classification of Student Academic Performance using Artificial Neural Networks," *SN Applied Sciences,* vol. 1, no. 982, 2019.

[10] A. Alsulaili and A. Refaie, "Artificial Neural Network Modeling Approach for The Prediction of Five-day Biological Oxygen Demand and Wastewater Treatment Plant Performance," *Water Supply,* vol. 21, no. 5, pp. 1861-1877, 2021.

[11] J. Rashid, S. Batool, J. Kim, M. W. Nisar, A. Hussain, S. Juneja and R. Kushwaha,

"An Augmented Artificial Intelligence Approach for Chronic Disease Prediction," *Frontiers in Public Health,* vol. 10, 2022.

[12] N. Alifiah, D. Kurniasari, Amanto and Warsono, "Prediction of COVID-19 Using the Artificial Neural Network (ANN) with K-Fold Cross-Validation," *Journal of Information Systems Engineering and Business Intelligence,* vol. 9, no. 1, pp. 16-27, 2023.

[13] M. Niazkar, "Revisiting the Estimation of Colebrook Friction Factor: A Comparison between Artificial Intelligence Models and C-W based Explicit Equations," *KSCE Journal of Civil Engineering,* vol. 23, pp. 4311-4326, 2019.

[14] D. H. N. Aini, D. Kurniasari, A. Nuryaman and M. Usman, "Implementation of Artificial Neural Network with Backpropagation Algorithm for Rating Classification on Sales of Blackmores in Tokopedia," *Jurnal Teknik Informatika,* vol. 4, no. 2, pp. 365-372, 2023.

[15] D. A. Nasution, H. H. Khotimah and N. Chamidah, "Perbandingan Normalisasi Data untuk Klasifikasi Wine Menggunakan Algoritma K-NN," *Computer Engineering Science and System Journal,* vol. 4, no. 1, pp. 78-82, 2019.

[16] Q. H. Nguyen, H.-B. Ly, H. S. Lan, N. Al-Ansari, V. H. Le, V. Q. Tran, I. Prakash and B. T. Pham, "Influence of Data Splitting on Performance of Machine Learning Models in Prediction of Shear Strength of Soil," *Mathematical Problems in Engineering,* vol. 2021, no. 6, 2021.

[17] I. O. Muraina, "Ideal Dataset Splitting Ratios in Machine Learning Algorithms: General Concerns for Data Scientists and Data Analysts," in *7th International Mardin Artuklu Scientific Researchs Conference*, Mardin, Turkey, 2022.

[18] L. Li, K. Jamieson, G. DeSalvo, A. Rostamizadeh and A. Talwalkar, "Hyperband: A Novel Bandit-Based Approach to Hyperparameter Optimization," *Journal of Machine Learning Research,* vol. 18, pp. 1-52, 2018.

[19] M. Adil, R. Ullah, S. Noor and N. Gohar, "Effect of Number of Neurons and Layers in an Artificial Neural Network for Generalized Concrete Mix Design," *Neural Computing and Applications,* vol. 334, pp. 8355-8363, 2022.

[20] H.-V. T. Mai, T.-A. Nguyen, H.-B. Ly and V. Q. Tran, "Investigation of ANN Model Containing One Hidden Layer for Predicting Compressive Strength of Concrete with Blast-Furnace Slag and Fly Ash," *Advances in Materials Science and Engineering,* vol. 2021, 2021.

[21] N. Srivastava, G. Hinton, A. Krizhevsky, I. Sutskever and R. Salakhutdinov, "Dropout: A Simple Way to Prevent Neural Networks from Overfitting," *Journal of Machine Learning Research,* vol. 15, pp. 1929-1958, 2014.

[22] V. Vijayalakshmi and K. Venkatachalapathy, "Deep Neural Network for Multi-Class Prediction of Student Performance in Educational Data," *International Journal of Recent Technology and Engineering,* vol. 8, no. 2, pp. 5073-5081, 2019.

[23] N. Rochmawati, H. B. Hidayati, Y. Yamasari, H. P. A. Tjahyaningtijas, W. Yustanti and A. Prihanto, "Analisa Learning Rate dan Batch Size pada Klasifikasi Covid Menggunakan Deep Learning dengan Optimizer Adam," *Journal Information Engineering and Educational Technology,* vol. 5, no. 2, pp. 44-48, 2021.

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[24] I. M. D. M. Sanjaya, "Klasifikasi Pneumonia pada Citra X-rays Paru-paru dengan Convolutional Neural Network," *Jurnal Nasional Teknik Elektro dan Teknologi Informasi,* vol. 9, no. 2, pp. 190-195, 2020.

[25] D. Puspitaningrum, Pengantar Jaringan Syaraf Tiruan, Yogyakarta: Andi, 2006.

[26] D. Kurniasari, R. V. Mahyunis, Warsono and A. Nuryaman, "Implementation of Artificial Neural Network (ANN) using Backpropagation Algorithm by Comparing Four Activation in Predicting Gold Prices," *Kumpulan Jurnal Ilmu Komputer,* vol. 10, no. 1, pp. 93-105, 2023.

[27] D. Kim, T. Kim, J. Jeon and Y. Son, "Soil-Surface-Image-Feature-Based Rapid Prediction of Soil Water Content and Bulk Density Using a Deep Neural Network," *Applied Sciences,* vol. 13, no. 7, 2023.