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Application of Neural Network to Predict Rupiah Exchange Rate Against Korean Won

Agung Saeful[1], Gifthera Dwilestari[2*], Ade Rizki Rinaldi[3]

[1] Teknik Informatika, STMIK IKIMI CIREBON
[2] Sistem Informasi STMIK IKIMI CIREBON
[3] Rekayasa Perangkat Lunak, STMIK IKIMI CIREBON
ggdwilestari@gmail.com*

Abstract

This study investigates the application of neural networks for predicting the exchange rate of the Indonesian Rupiah against the Korean Won, addressing the challenges posed by currency fluctuations in international trade and investment. The research employs a data mining approach utilizing historical exchange rate data, which allows the neural network to identify complex patterns that traditional forecasting methods may miss. The model is developed using RapidMiner software, facilitating data preprocessing, transformation, and evaluation. The outcomes show that the predictions were quite accurate, as indicated by a low prediction error rate. The findings suggest that the neural network model not only provides reliable forecasts but also maintains consistent performance over time. This research contributes to the growing field of artificial intelligence in finance, highlighting the potential of advanced predictive models to enhance decision-making processes in the context of global economic interactions. The study underscores the importance of integrating technology with economic analysis to better navigate the complexities of currency exchange and its implications for financial risk management.

Keywords: *Artificial Intelligence; Currency Exchange; Neural Networks; Prediction Accuracy; Rupiah-Korean Won*

1. Introduction

Currency exchange rates often experience fluctuations or erratic changes. This is an important concern for many parties, especially in the world of international trade and investment. Changes in exchange rates can affect the prices of imported and exported goods, as well as capital flows in and out of a country. Therefore, predicting exchange rate movements becomes very important so that financial risks can be minimized.

In this case, th Currency exchange rates often experience fluctuations or erratic changes. This is an important concern for many parties, especially in the world of international trade and investment. Exchange rate fluctuations may have an impact on the costs of both imported and exported items, as well as capital flows in and out of a country [1]. Therefore, predicting exchange rate movements becomes very important so that financial risks can be minimized. Rupiah to Korean Won exchange rate is one currency pair to watch, given the increasingly close trade relationship between Indonesia and South Korea. However, Numerous factors frequently affect exchange rates, such as economic policies, global market conditions, and interest rate changes, making it difficult to predict accurately [2].

Along with the development of technology, artificial intelligence methods, such as neural networks, are starting to be used to help predict exchange rate movements. neural networks are able to learn from historical data and find patterns that may not be seen by traditional methods. Therefore, this method is considered more capable of providing more accurate predictions in complex situations [3], [4]. This research aims to apply Neural Network in predicting the volatility of Rupiah exchange rate against Korean Won by utilizing historical data and related economic variables.

1.1. Data mining

Data mining is the process of gathering and analyzing data to find important information, patterns, and hidden trends. Using algorithms and statistical techniques, data mining helps us process massive data sets to obtain valuable information . The goal is to discover things that are not immediately apparent, such as patterns in customer behavior, relationships between variables, or predictions of future trends [5].

1.2. RapidMiner

RapidMiner is a data science software application developed by the Rapid-I company. It is used for business and commercial purposes as well as for education, research, training and application development, deep learning, text mining, and predictive analytics. Users can use

RapidMiner to perform all machine learning processes, such as data preparation, result visualization, validation, and optimization. In addition, RapidMiner is developed using innovative and reliable models, and has various features that support rapid prototype development [6].

1.3. Neural network

Neural Network is one of the techniques in machine learning that replicates the information processing mechanisms of the human brain. By using historical exchange rate data, Neural Network can learn to recognize hidden patterns that may not be visible to traditional methods. Therefore, the application of Neural Network in exchange rate prediction is expected to provide more accurate and reliable results [7].

1.4. Windowing

Time series data can be transformed by the windowing operator into a set of sample windows for machine learning processing. The last index value of the time series in the relevant window is additionally added when windowing is used. Additionally, an attribute called window id with the matching window number is added if the index is not specified. The default example explains the windowing behavior. Duration or time period are used to set time-based windowing parameters. The newly constructed "custom window" input port requires an additional exampleSet for "custom" windows. All time series, including nominal, numeric, and time series with date values, can be worked with by this operator [8].

1.5. Root Mean Square Error (RMSE)

Root Mean Square Error (RMSE) is an important metric in data analysis and machine learning used to measure model prediction error. A low RMSE indicates that the model is making more accurate predictions and fitting the data. Conversely, higher values indicate more significant errors and less accurate forecasts [9], [10].

2. Research Methodology

This research uses quantitative methods with an experimental approach through the RapidMiner platform, and is developed based on the KDD (Knowledge Discovery in Databases) framework [8], [11], [12], [13], [14]. The data used is taken from the official website of Bank Indonesia, covering the historical period from October 28, 2019 to October 25, 2024. This time span was chosen to allow the neural network model to predict the volatility of the Rupiah exchange rate against the Korean Won. The research stages applied follow a systematic process to obtain patterns and predictions from the available data .

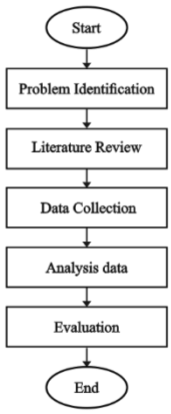

Fig. 1: Research Workflow

The following is an explanation for each stage in Figure 1: Research Workflow:

1. Problem Identification
   This research begins with the first step of identifying the main problem to be solved. In this case, the focus of the problem is how to utilize neural network models to improve the accuracy of making predictions about how the Rupiah would fluctuate in value relative to the Korean Won (IDR/KRW).
2. Literature Review
   Before entering the analysis stage, a literature review was conducted to understand the methods and approaches that have been applied in previous studies.
3. Data Collection
   This study's data came from the official website of bank Indonesia, this time span can cover the historical period from the period starting from October 28, 2019 to October 25, 2024. This data is downloaded in CSV or Excel format and provides a comprehensive overview of the volatility of the rupiah exchange rate against the Korean won.
4. Analysis Data
   The data analysis stage of the KDD method and modeling is carried out using RapidMiner software which facilitates the application of neural networks in predicting and assisting in selecting parameters and evaluating prediction results in the form of rsme. The steps are Data preprocessing, Data Transformation, Data mining, and Evaluation of results.

5. Evaluation
   After the model is applied, its performance is evaluated to measure how good the predictions are. RMSE (Root Mean Square Error) is used as one measure of prediction error.

3. Results and Discussion

3.1. Data Selection

The process begins with a careful selection of data, where we collect historical data from the official website of Bank Indonesia. After that, the data was separated into two categories: testing data and training data. The training data covers the period from October 28, 2019 to September 30, 2024, consisting of 1,210 data entries with attributes such as “Value”, “Sell rate”, “Buy rate”, and “Date”. These attributes will be used in training the model to help predict future exchange rate changes. The results are reflected in Table 1.

Table 1: Real data of rupiah exchange rate against Korean won

NO	Value	Sell rate	Buy rate	Date
1	1,00	11,37	11,26	09/30/2024
2	1,00	11,36	11,25	09/29/2024
3	1,00	11,35	11,23	09/28/2024
4	1,00	11,28	11,17	09/27/2024
5	1,00	11,33	11,22	09/26/2024
6	1,00	11,38	11,27	09/25/2024
…	…	…	…	…
…	…	…	…	…
1205	1,00	12,14	12,01	11/4/2019
1206	1,00	12,12	11,99	11/1/2019
1207	1,00	12,12	12,00	10/31/2019
1208	1,00	12,08	11,96	10/30/2019
1209	1,00	12,08	11,96	10/29/2019
1210	1,00	12,05	11,93	10/28/2019

The test data was selected from the period November 1, 2024 to November 14, 2024 with the main purpose of measuring the accuracy of the prediction model that has been built previously. This data serves as a verification tool, to ascertain whether the trained neural network model is able to correctly predict exchange rate changes after the training process. This test is crucial for evaluating the model's dependability and efficacy in actual circumstances, where new data is encountered without prior information.The results are reflected in Table 2

Table 2: Testing data

Date	Exchange rate
11/14/2024	?
11/11/2024	?
11/10/2024	?
11/09/2024	?
11/08/2024	?
…	…
…	…
11/01/2024	?
10/31/2024	11,46
10/30/2024	11,43

3.2. Data Preprocessing

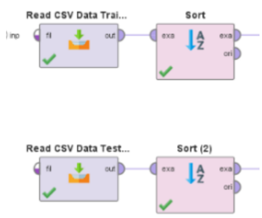

Fig. 2: Data Preprocessing

Once the data is selected, the next step is the preprocessing stage, which is very important to ensure that the data used is ready to be processed in the machine learning model. At this stage, the data is imported from a CSV file using the Read CSV operator in the RapidMiner platform. This process allows the raw data to be entered into the analysis environment.

After successfully importing the data, in the traning data, attribute selection is carried out, which is the selection of variables that are considered relevant for the model. Less significant variables, such as “Value” and “Buy rate,” were removed from the dataset, leaving only the “Date” and “Sell rate” attributes. The attribute “Sell rate” change name to “ Exchange rate”. This step aims to simplify the model by focusing only on the variables that have the most impact on the prediction [15]. By performing this filtering, the model becomes more efficient and can provide more accurate prediction results, as irrelevant variables have been removed. The results are reflected in Table 3

Table 3: Data training

Date	Exchange rate
09/30/2024	11,37
09/29/2024	11,36
09/28/2024	11,35
09/27/2024	11,28
09/26/2024	11,33
…	…
…	…
11/01/2019	12,12
10/31/2019	12,12
10/30/2019	12,08
10/29/2019	12,08
10/28/2019	12,05

After the attribute selection process is complete, the data is then sorted by date using the sort operator. This sorting is necessary to preserve the data's chronological sequence, which is indispensable in temporal analysis, especially when using prediction models that rely on historical data. By maintaining the correct time sequence, the model can more easily recognize patterns of exchange rate movement over time, which in turn improves the accuracy of the prediction. In addition, since the data used in this study does not contain missing values, the missing value replacement or imputation step is not necessary. This facilitates the preprocessing process, as the data is already in a relatively clean condition and ready to be used without the need for additional handling to deal with the issue of missing values. All steps in this preprocessing stage are done to ensure that the data entered into the model is in an optimal form, so that the analysis and predictions carried out later can run more smoothly and provide accurate results.

3.3. Data Transformation

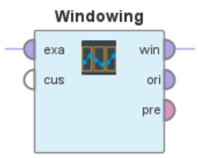

Fig. 3: Operator Windowing

After the preprocessing stage is complete, the next step is data transformation using the windowing operator, which serves to create a periodically moving time window along the historical data of the Rupiah exchange rate against the Korean Won. This operator shifts the data from one observation to the next, so that the model can learn the pattern of change from the previous data. With windowing, the model sees not only one data point at each observation, but also several time periods before it, which allows the neural network model to better capture temporal dynamics. This process is very important as past movements are often indicative of future movements. By effectively utilizing historical information, models can recognize more complex patterns, such as trends, seasonal fluctuations, or responses to economic changes. This transformation helps the model become smarter in understanding changes in exchange rates over time, ultimately improving the accuracy of predictions [8].

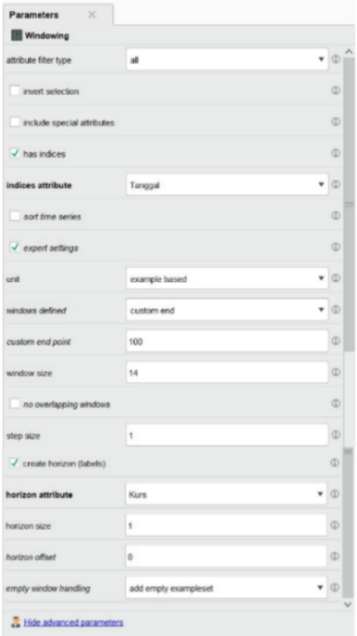

Fig. 4: Parameter Windowing

The parameter settings for the windowing operator in RapidMiner are designed to shape the time window that will be used in the time series prediction model. Here is a brief explanation of each setting the results are reflected in Figure 3.

Windowing begins by considering all data attributes without exception, with Date as an index to sort the data chronologically. The data was sorted by time to maintain consistency, using an example-based approach where each step is measured against individual observations.The time window was set to reach a custom endpoint at the 100th observation, with a window size of 14, which included the previous 14 observations for analysis. The step size is 1, so the time window shifts by one observation at each iteration. The rate is used as the horizon or prediction label, with a horizon size of 1, which means the prediction is done one step ahead. If there is an empty window, empty data will be added automatically to keep the process smooth.

3.4. Data Mining

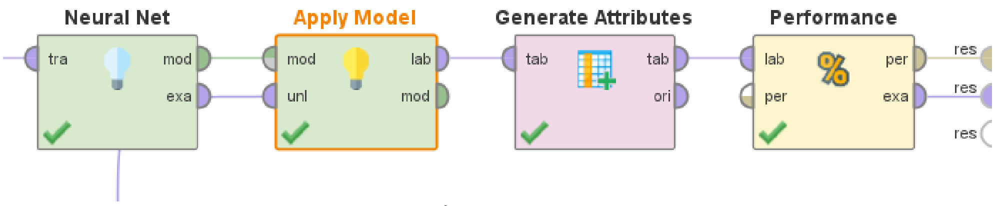

Fig. 5: Data mining

The initial stage began with the use of a Neural Net operator where a neural network model was built and trained using the training data. The model was trained through 1000 training cycles with a learning rate setting of 0.09 and momentum of 0.09. The network also utilizes 6 hidden layers that help the neural network in recognizing more complex data patterns.

The Apply Model operator is used to apply the neural network model to unlabeled data once it has been trained. At this point, new data is labeled using predictions made by the trained model, producing data with labels based on predictions.

The next process uses the Generate Attributes operator to calculate the prediction interval. In this stage, the lower and upper bounds of the prediction are calculated by considering the margin of error as well as a confidence level of 95%. In other words, the generated predictions are expected to fall between the upper and lower bounds with a high level of confidence. The RMSE used in this calculation reflects the average error of the prediction. The results Parameter Generate Attributes operator are reflected in Figure 5.

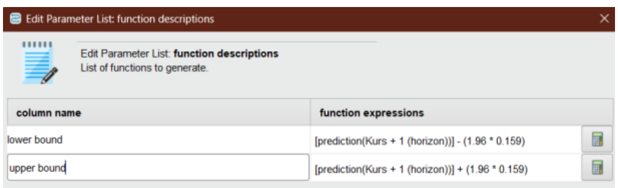

Fig. 6: Parameter Generate Attributes operator

The last stage is model evaluation with the Performance operator. At this stage, The model's performance is assessed through comparison the prediction results obtained from the labeled data with the actual label. This evaluation aims to assess how well the neural network model predicts the expected results, thus providing an overview of the effectiveness and reliability of the model in making predictions.

In the data mining process, neural networks are used to predict prices based on available data. This process produces two main outputs, namely the price prediction and the prediction error rate measured using RMSE (Root Mean Square Error). Price prediction is used to estimate future values, while RMSE serves as a measure of the accuracy of the prediction.

3.5. Evaluation

In this study, the RMSE value obtained was 0.159 with a deviation of +/- 0.000. This low RMSE value indicates that the prediction model has a very small error rate, which means that the predictions generated are very close to the true value. A deviation close to zero indicates that the predictions generated by the model are not only accurate, but also consistent over time. Thus, the model is not only able to provide precise prediction results, but also maintains stable performance, making it reliable for predicting exchange rate movements in the long run.

In addition to evaluating its performance, the model also produces a prediction of the exchange rate of Rupiah against Korean Won for the period November 1, 2024 to November 14, 2024. The results of this prediction are presented in Table 4, which provides a detailed overview of the exchange rate fluctuations over the period. With these predictions, the model not only demonstrates its internal performance, but also provides data that can be used for further analysis or for consideration in economic and financial decision-making.

Table 4 : Prediction results

Date	Exchange rate	Lower bound	Upper bound
01/11/2024	11.997	11.685	12.308
02/11/2024	11.902	11.591	12.214
03/11/2024	11.896	11.584	12.207
04/11/2024	11.972	11.660	12.283
05/11/2024	11.836	11.525	12.148
06/11/2024	11.970	11.659	12.282
07/11/2024	11.906	11.595	12.218
08/11/2024	11.847	11.536	12.159
09/11/2024	11.946	11.634	12.257
10/11/2024	11.824	11.512	12.136
11/11/2024	11.853	11.542	12.165
12/11//2024	11.866	11.554	12.177
13/11/2024	11.852	11.541	12.164
14/11/2024	11.808	11.496	12.120

The results of the prediction of the Rupiah exchange rate against the Korean Won for the period 1 November 2024 to 14 November 2024 are then visualized in the form of a graph. This graph provides a visual representation of the predicted exchange rate fluctuations during the period, making it easier to see the movement trends and patterns of exchange rate changes more clearly. This visualization not only helps clarify the prediction results, but also provides a deeper insight into the potential changes in the exchange rate. The results prediction chart are reflected in Figure 6.

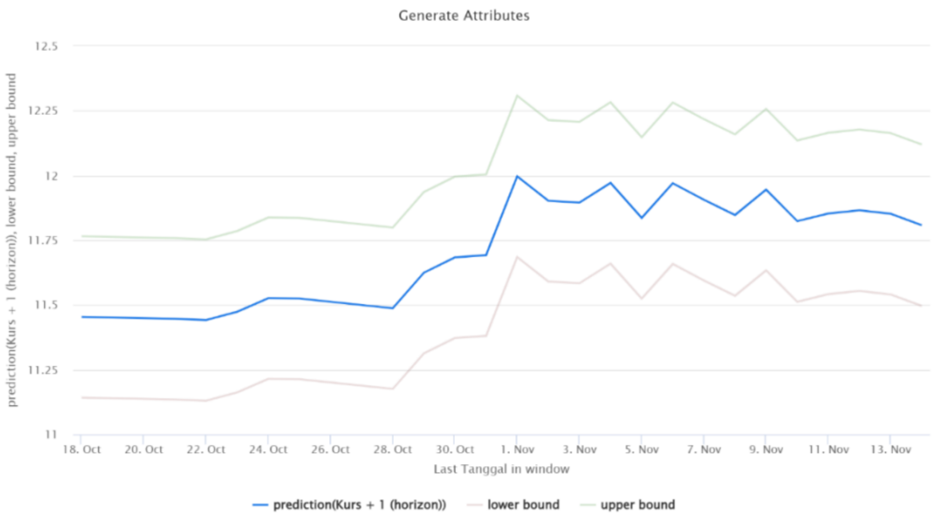

Fig. 7: Prediction chart

4. Conclusion

In conclusion, this study represents a major breakthrough in the use of neural networks for predicting the exchange rate of the Indonesian Rupiah against the Korean Won. By leveraging historical data and employing advanced data mining techniques, the research successfully identifies complex patterns that traditional forecasting methods may overlook. The model achieved a low Root Mean Square Error (RMSE) of 0.159, indicating a high level of accuracy in its predictions. This low error rate not only demonstrates the reliability of the neural network approach but also suggests its potential for consistent performance over time, making it a valuable tool for stakeholders in international trade and investment.

Moreover, the findings of this research highlight the importance of integrating artificial intelligence with financial analysis to enhance decision-making processes. The ability of the neural network model to provide precise predictions for future exchange rate movements offers significant benefits for risk management in the context of fluctuating currency values. As the global economy continues to evolve, the insights gained from this study pave the way for further exploration and refinement of predictive models, ultimately contributing to a deeper understanding of currency dynamics and their implications for international commerce.

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