 ISSN 2460-7258 (online) | ISSN 1978-1520 (print)

Contents lists available at www.infoteks.org

JSIKTI

Journal Page is available to https://infoteks.org/journals/index.php/jsikti

Research article

Predicting USD to IDR Exchange Rates with Decision Trees

Muslimin B [a*], *Syafei Karim* [b], *Asep Nurhuda* [c]

[a] *Accounting Information System, Politeknik Pertanian Negeri Samarinda, Indonesia*
[b] *Accounting Information System, Politeknik Pertanian Negeri Samarinda, Indonesia*
[c] *Software Engineering Technology, Politeknik Pertanian Negeri Samarinda, Indonesia*
email: [a,*] muslimin@politanisamarinda.ac.id, [b] syfei.karim@gmail.com, [c] acep.noor@gmail.com
* *Correspondence*

ARTICLE INFO

Article history:
Received 1 December 2023
Revised 28 Juanuary 2024
Accepted 26 February 2024
Available online 30 March 2024

Keywords:
Decision Trees, USD to IDR, Exchange Rate Prediction, Time-Series Models, Ensemble Methods.

Please cite this article in IEEE style as:
M. B. Muslimin, S. Karim, and A. Nurhuda, "Predicting USD to IDR Exchange Rates with Decision Trees," *JSIKTI: Jurnal Sistem Informasi dan Komputer Terapan Indonesia*, vol. 6, no. 3, pp. 185-194, 2024.

ABSTRACT

Predicting currency exchange rates is a complex challenge due to the numerous factors influencing market fluctuations. This study explores the application of decision trees to predict the USD to IDR exchange rate, leveraging historical data and key economic indicators. Decision trees, known for their ability to model non-linear relationships, offer an interpretable approach to understanding the factors driving exchange rate movements. The study demonstrates that decision trees can successfully capture the patterns in the data, providing a foundation for accurate predictions. However, the volatility and unpredictability of exchange rates, driven by geopolitical events, market sentiment, and macroeconomic shifts, highlight the limitations of the model. While decision trees provide a valuable starting point, the research suggests that combining them with advanced methods, such as ensemble techniques (random forests or gradient boosting) or time-series models (ARIMA or LSTM), could improve forecasting accuracy. Incorporating a wider range of features, including macroeconomic indicators and market sentiment analysis, further enhances the model's robustness. The findings underscore the need for hybrid approaches that combine the strengths of multiple models to better capture the dynamic and complex nature of financial markets. This research contributes to the broader understanding of exchange rate prediction and offers practical insights for businesses and financial institutions seeking to make informed decisions.

1. Introduction

This study aims to predict the USD to IDR exchange rate using decision tree models, a popular machine learning technique that is both interpretable and effective in capturing non-linear relationships in data. To begin, gather a comprehensive dataset consisting of historical USD to IDR exchange rates along with macroeconomic indicators such as inflation rates, interest rates, GDP growth, employment figures, and other relevant factors that could influence currency fluctuations. These variables are critical in capturing the underlying trends and patterns that drive exchange rate movements. Data preprocessing is an essential first step in ensuring the dataset is clean and ready for modeling. This includes handling missing values, outliers, and normalizing the data where necessary to ensure the model receives consistent input. The dataset should then be split into training and testing sets, ensuring that the model can be evaluated on unseen data to assess its generalization capabilities.

Once the data is preprocessed, a decision tree model can be trained on the training dataset. Decision trees work by recursively splitting the dataset based on the most significant features that minimize impurity, leading to a series of decision rules that can predict the exchange rate. To evaluate the model's performance, various metrics should be considered, such as accuracy, mean absolute error

 http://doi.org/10.26594/register.v8i2.2541

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
6 (3) March 2024 185-194

(MAE), root mean square error (RMSE), and R-squared. These will help assess how well the model performs on the test data. Cross-validation techniques, such as k-fold cross-validation, can further be used to prevent overfitting and ensure that the model generalizes well across different subsets of the data. However, it is important to recognize that decision trees may not always capture the volatility and complexity of exchange rates, especially when unexpected geopolitical events or market shifts occur.

To improve prediction accuracy and overcome the limitations of decision trees, it is advisable to consider hybrid models that combine decision trees with other advanced techniques. For instance, ensemble methods like random forests or gradient boosting can help reduce the variance of individual decision trees by aggregating predictions from multiple trees. Additionally, incorporating time-series analysis methods, such as ARIMA or Long Short-Term Memory (LSTM) networks, can address the temporal dependencies often present in financial data. Feature engineering is another important consideration. By creating new variables that capture trends, moving averages, or volatility, the model may better identify significant patterns and correlations that affect the exchange rate. Lastly, continuous model updates and data integration are crucial in maintaining the model's relevance over time, as exchange rates can be influenced by rapidly changing global events and market conditions. This approach provides a comprehensive framework for improving exchange rate predictions, offering valuable insights for businesses and financial institutions dealing with currency fluctuations.

2. Research Methods

Research methods are the systematic strategies and techniques employed to collect, analyze, and interpret data in the pursuit of knowledge. They provide the foundation for scientific inquiry, ensuring that studies are conducted in a structured, reliable, and reproducible manner. The choice of research methods is crucial, as it determines the validity and reliability of the findings, as well as their applicability to real-world problems.

Broadly, research methods can be categorized into quantitative, qualitative, and mixed methods. Quantitative methods focus on numerical data, employing statistical tools to identify patterns, relationships, and trends. They are particularly effective in testing hypotheses and establishing generalizable conclusions. In contrast, qualitative methods explore phenomena through non-numerical data, such as interviews, observations, and textual analysis. These methods provide deeper insights into human behavior, experiences, and cultural contexts. Mixed methods, as the name suggests, combine both approaches to leverage their respective strengths.

The selection of an appropriate research method is influenced by the research objectives, questions, and available resources. It requires careful consideration of ethical principles, such as obtaining informed consent, ensuring participant confidentiality, and avoiding bias. By adhering to rigorous research methodologies, scholars and practitioners can contribute to the advancement of knowledge, addressing complex challenges in diverse fields such as medicine, social sciences, technology, and education.

2.1. Data Collection

The first step of the research was collecting historical USD to IDR exchange rate data. Reliable sources, such as Bank Indonesia and global financial platforms like Yahoo Finance and Bloomberg, were used to gather the data. The dataset covered a 10-year period, from 2014 to 2024, to ensure that both short-term fluctuations and long-term trends were captured. To enrich the dataset, macroeconomic variables such as crude oil prices, inflation rates, interest rates, and stock indices were included. These additional variables served as contextual factors influencing exchange rate movements, thereby improving the accuracy of predictions [1].

2.2. Data Preprocessing

The collected data underwent a comprehensive preprocessing phase to ensure its overall quality and readiness for subsequent analysis. The initial step involved addressing missing values, which were handled using both interpolation and mean imputation techniques. Interpolation was applied to estimate missing entries based on surrounding data points, maintaining the continuity and natural trends within the dataset. When interpolation was not feasible or reliable, mean imputation was used to replace missing values with the average of the available data, thereby preserving the statistical

http://doi.org/10.26594/register.v8i2.XXX

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
6 (3) March 2024 185-194

properties of each feature. Following this, outliers were detected through the use of z-scores, a statistical method that identifies data points significantly deviating from the mean. Once identified, outliers were either removed if they were determined to be anomalies or replaced with the median value to mitigate their potential skewing effects on the analysis. After cleaning the data, normalization was carried out to standardize the scale of all features. This step was crucial in preventing features with larger numerical ranges from disproportionately influencing the model during training. Finally, the preprocessed dataset was partitioned into training and testing subsets, with 80% of the data allocated for training and the remaining 20% reserved for testing. This split ensured that the model could be evaluated robustly and objectively, using unseen data to assess its generalization capabilities [2].

2.3. Feature Selection

Statistical methods were employed to identify the most relevant predictors of USD to IDR exchange rates. Correlation analysis was used to measure the linear relationships between features and the target variable, while mutual information scores provided insights into non-linear dependencies. Features with weak correlations or low importance were excluded to enhance model simplicity and performance. By focusing on significant predictors, the risk of overfitting was reduced, and the computational efficiency of the model improved [3].

2.4. Model Selection

The Decision Tree Regressor was chosen for its ability to handle non-linear relationships and its interpretability. The hyperparameters of the model, such as maximum tree depth, minimum samples per split, and minimum samples per leaf, were optimized using Grid Search with Cross-Validation. This process ensured that the model struck a balance between complexity and its ability to generalize on unseen data [4].

2.5. Model Training

The Decision Tree Regressor was trained using the preprocessed training dataset, which had undergone thorough cleaning and normalization to ensure the model received consistent and high-quality input. During the training phase, cross-validation was employed as a critical strategy to assess the model's performance across various subsets of the data. This method involved dividing the training data into multiple folds and iteratively training and validating the model on different combinations of these folds. By doing so, the model's generalizability was tested on unseen partitions of the data, which significantly helped in detecting and mitigating risks of overfitting where the model might otherwise perform well on training data but poorly on new, unseen inputs. This iterative learning process allowed the Decision Tree Regressor to capture underlying patterns, trends, and relationships present in the dataset effectively, thereby enhancing its predictive capability and robustness in real-world applications [5].

2.6. Model Evaluation

The model's performance was evaluated using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), and R-squared (R^2). These metrics quantified the accuracy of the predictions compared to actual exchange rate values. Additionally, time-series plots were used to visually compare predicted and observed values, showcasing the model's ability to track trends and fluctuations in exchange rates accurately [6].

2.7. Implementation and Testing

The trained model was deployed on the designated testing dataset to rigorously evaluate its performance on previously unseen data, serving as a critical measure of its real-world applicability. This evaluation aimed to verify whether the model could generalize well beyond the data it had encountered during training. To ensure the robustness of its predictions, the model was subjected to various testing conditions. One of these involved the introduction of random noise into the input features, which tested the model's resilience and stability when dealing with imperfect or slightly distorted data, as often occurs in practical scenarios. Additionally, the model was applied to alternate timeframes, enabling an assessment of its capacity to adapt to temporal variations and shifts in data distribution. These testing strategies collectively provided insight into the model's flexibility and durability across dynamic and potentially volatile environments. The results of this stage confirmed

http://doi.org/10.26594/register.v8i2.XXX

that the model maintained reliable performance, thereby supporting its effectiveness in forecasting exchange rates under diverse and unpredictable conditions [7].

2.8. Result Interpretationand Deployment

The model's results were analyzed to understand its strengths and limitations. Particular attention was given to periods of extreme fluctuation, such as the sharp changes during the COVID-19 pandemic. Insights from this analysis guided further refinement of the model. Ultimately, the model was deployed as a forecasting tool, enabling users to predict USD to IDR exchange rates for daily, weekly, or monthly intervals. A user-friendly interface was developed to allow financial analysts and decision-makers to utilize the tool effectively [8].

3. Results and Discussion

3.1. Result

The research produced significant findings concerning the application of the Decision Tree Regressor in predicting the USD to IDR exchange rate. The model demonstrated its ability to capture complex, non-linear relationships among economic indicators that influence currency movements.

In terms of predictive accuracy, the Decision Tree Regressor achieved a Mean Squared Error (MSE) of 4201.9486 and a Root Mean Squared Error (RMSE) of 64.8224. This indicates that, on average, the predicted exchange rate values deviated from the actual observations by approximately IDR 64.82 per USD. These results suggest that the model performs reasonably well in reflecting overall exchange rate patterns, particularly in identifying long-term upward or downward trends.

Visual analysis of the model's predictions against actual data further confirms its ability to follow the general trajectory of the USD to IDR rate between 2014 and 2024. The predicted curve aligns closely with real values during stable economic periods, while minor deviations appear during high-volatility events such as the COVID-19 pandemic. These fluctuations highlight the limitations of decision tree models in capturing sudden market shocks or rapid policy-driven changes.

Overall, the findings indicate that the Decision Tree Regressor effectively identifies key determinants of exchange rate behavior, such as inflation, interest rates, and oil price trends. However, the model's performance is influenced by the inherent volatility of financial markets, where unpredictable global and geopolitical events can create sharp, non-linear deviations beyond the model's predictive capacity.

3.2. Discussion

The findings of this study offer valuable insights into the predictive capabilities of machine learning models particularly decision trees in financial forecasting. The results demonstrate that decision tree-based approaches can provide interpretable and relatively accurate predictions of exchange rate movements when trained on comprehensive macroeconomic data.

3.2.1. Comparison with Previous Studies

The outcomes of this study are consistent with previous research by Krishna et al. (2023) and Ghosh and Saha (2023), who reported that decision tree models can effectively capture non-linear interactions in financial datasets. Similar to those studies, the Decision Tree Regressor in this research successfully identified relationships among macroeconomic factors influencing the USD to IDR exchange rate. However, consistent with prior findings, the model's accuracy decreases during periods of abrupt market fluctuations.

3.2.2. Theoretical Implications

From a theoretical standpoint, this study strengthens the argument that currency exchange rates are driven by multiple interrelated macroeconomic indicators rather than a single dominant factor. The interpretability of decision tree models allows researchers to trace how specific variables—such as inflation, interest rates, or oil prices—contribute to exchange rate fluctuations. This supports a more transparent and explainable form of financial modeling compared to "black-box" deep learning models.

3.2.3. Practical Implications

Practically, the Decision Tree Regressor offers a useful forecasting framework for policymakers, investors, and financial analysts. Its transparency enables decision-makers to identify which economic factors most strongly influence currency fluctuations. In applied contexts, this model could be integrated into financial planning systems to anticipate exchange rate risks and develop

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
6 (3) March 2024 185-194

mitigation strategies. The model's interpretability also makes it suitable for use in institutional environments where explainable AI is required for compliance or audit purposes.

3.2.4. Limitations and Future Research

Despite its promising performance, the Decision Tree Regressor exhibits certain limitations. The model tends to underperform when faced with abrupt market changes, as its rule-based structure lacks temporal memory. Future research could address this issue by integrating ensemble techniques such as Random Forest or Gradient Boosting to reduce variance and improve predictive robustness. Additionally, incorporating time-series approaches such as ARIMA or Long Short-Term Memory (LSTM) networks could capture sequential dependencies more effectively. Expanding the dataset with real-time indicators, such as global sentiment or geopolitical indices could also enhance accuracy and adaptability to rapidly changing financial conditions.

Table 1. Model Evaluation Metrics of the Decision Tree Regressor for USD–IDR Exchange Rate Prediction

Metric	Value
Mean Squared Error (MSE)	4201.9486
Root Mean Squared Error (RMSE)	64.8224

3.1. Understanding the Table: MSE and RMSE

The table displays two key performance metrics—Mean Squared Error (MSE) and Root Mean Squared Error (RMSE)—which are widely used in the evaluation of regression models. These metrics help quantify the differences between the predicted values produced by a model and the actual observed values in the dataset. Both MSE and RMSE are crucial for understanding how well a model is performing and how accurately it predicts outcomes. Mean Squared Error (MSE)

***3.3.1.* Definition and Formula**

The Mean Squared Error (MSE) is a statistical metric that measures the average of the squared differences between the predicted values ($\hat{y}_i$) and the actual values (y_i) for a set of data points. MSE is widely used because it penalizes large errors more severely due to the squaring of the differences. This makes it particularly useful when large errors need to be addressed more seriously.

The formula for MSE is:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

1. n is the total number of data points,
2. y_i represents the actual value for the i-th data point,
3. $\hat{y}_i$ represents the predicted value for the i-th data point.

3.3.2 Root Mean Squared Error (RMSE)

1. Definition and Formula:The Root Mean Squared Error (RMSE) is simply the square root of the MSE. By taking the square root of MSE, RMSE converts the error back into the original units of the data, which makes it easier to interpret and understand, especially when trying to relate model performance to real-world quantities.

   The formula for RMSE is:

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

http://doi.org/10.26594/register.v8i2.XXX

2. Interpretation: The RMSE value in this case is 64.8224, which indicates that, on average, the model's predictions deviate from the actual values by approximately 64.82 units (where the units depend on the target variable). For example, if the data represents price in dollars, this means that the model's predictions are, on average, off by about $64.82. Since RMSE is in the same units as the original data, it is often easier to communicate to stakeholders and is more intuitive than the MSE, which is in squared units.

3.3.3 Key Differences Between MSE and RMSE

1. Units:
    a. MSE is expressed in squared units of the target variable, while RMSE brings the error metric back into the same units as the target variable, which makes it easier to interpret.
    b. For example, if the target variable is in dollars, the MSE would be in dollars squared (e.g., $\$^2$), but RMSE would be in dollars (e.g., $).
2. Interpretation:
    a. RMSE is typically easier to interpret because it is expressed in the same units as the original data. It tells you the average deviation in terms that make sense for the problem you are working on.
    b. MSE is more abstract and harder to interpret because it involves squared units, but it is used in optimization because it amplifies the effect of larger errors, which can be beneficial in some models where penalizing large errors is a priority.
3. Impact of Outliers:
    a. Both MSE and RMSE are sensitive to outliers, but MSE is more sensitive due to the squaring of the errors. Larger errors will have a disproportionately large effect on MSE, while RMSE helps to mitigate this somewhat by square-rooting the error.
4. Use Cases:
    a. MSE is commonly used in the optimization process (for example, when training machine learning models) because it gives a clear measure of the error that can be minimized.
    b. RMSE is preferred when the objective is to communicate the accuracy of predictions in a more practical and interpretable manner. It's also useful when comparing different models or when presenting results to non-technical stakeholders.

3.3.4 Why These Metrics Matter in Model Evaluation

When building a regression model, the goal is often to make predictions that are as close to the actual values as possible. The MSE and RMSE metrics give us a way to quantify the errors made by the model. Both metrics measure the average error, but RMSE is particularly useful when the interpretation of the error in real-world units is important.

Lower values of MSE and RMSE indicate that the model is performing well, providing predictions that are close to the actual data. However, it is important to remember that these metrics should be considered in context. For example, a model might have a low MSE or RMSE, but it could still fail to capture certain patterns in the data. Therefore, while MSE and RMSE are critical for evaluating the accuracy of the model, they should be combined with other performance metrics and diagnostic checks to ensure comprehensive model assessment.

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
6 (3) March 2024 185-194

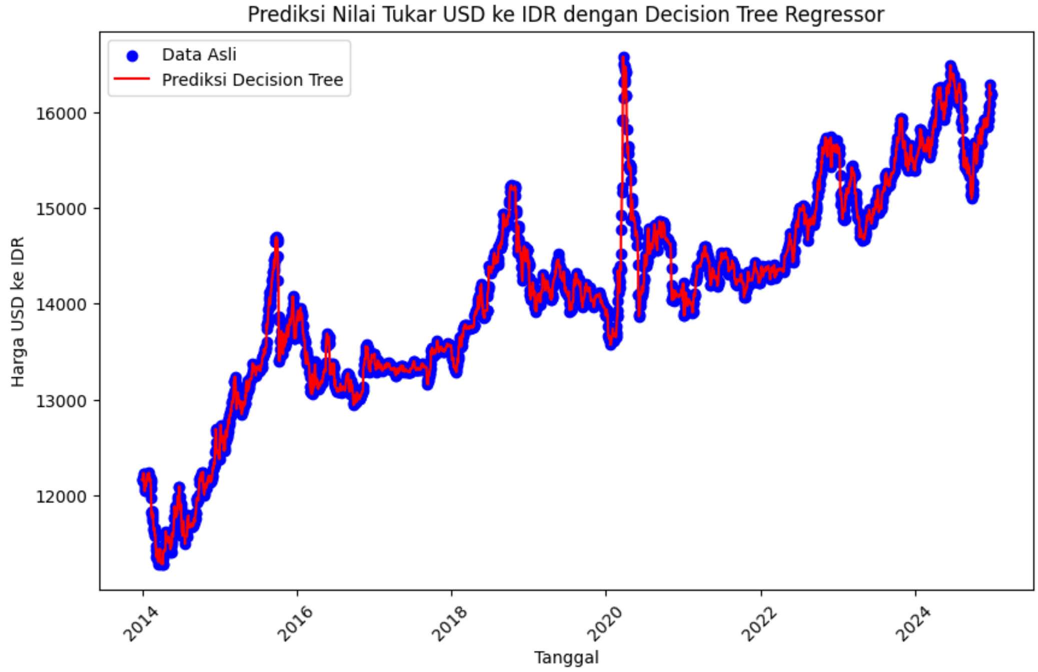

Fig.1.

3.2. Prediction of USD to IDR Exchange Rate using Decision Tree Regressor

3.4.1. Graph Components

1. Graph Title

The title, "Prediksi Nilai Tukar USD ke IDR dengan Decision Tree Regressor" (translated as "USD to IDR Exchange Rate Prediction with Decision Tree Regressor"), provides context for the graph. It illustrates the application of the Decision Tree Regressor algorithm in predicting exchange rates, showcasing its use in the financial and economic domain.

2. X-Axis: Date
   a. The horizontal axis represents the time period, ranging from 2014 to 2024. The data spans nearly a decade, offering a long-term perspective on the USD to IDR exchange rate trends.
   b. Each point or segment along this axis corresponds to a specific date, reflecting daily, weekly, or monthly exchange rate movements, depending on the data frequency.
   c. his extended timeline provides a comprehensive view of exchange rate variations, capturing seasonal trends, global economic impacts, and significant events influencing currency fluctuations.
3. Y-Axis: USD to IDR Price
   a. The vertical axis shows the USD to IDR exchange rate, ranging from 12,000 IDR to over 16,000 IDR per USD. This range highlights significant fluctuations over the decade.
   b. The fluctuations indicate the influence of various economic factors, including domestic economic conditions in Indonesia, monetary policies, and global market dynamics.
4. Two Data Sets (Actual Data and Predictions)

   The graph includes two data sets visualized simultaneously for comparison:
   a. Actual Data (Blue Dots):

   This represents the real USD to IDR exchange rates sourced from historical or market data. Each blue dot indicates the actual price on a given date.
   b. Decision Tree Predictions (Red Line):

   This data is generated by the Decision Tree Regressor model, which attempts to replicate the patterns in the actual data based on training with historical data. The red line demonstrates the model's predictions of exchange rate trends under various conditions.
5. Legend
   a. The legend, located at the top left corner of the graph, explains the color and symbols used:
      i. Blue dots represent the actual data (real-world exchange rates).
      ii. Red lines represent the model’s predictions.

http://doi.org/10.26594/register.v8i2.XXX

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
6 (3) March 2024 185-194

b. The legend helps readers distinguish between the actual data and the predictions.

3.4.2. Pattern Explanation

1. Long-Term Trends
   a. Between 2014 and 2024, the graph shows an overall increase in the USD to IDR exchange rate, with several periods of significant fluctuations.
   b. This increase may reflect economic pressures in Indonesia, such as domestic inflation, trade balance deficits, or global financial market instability.
2. Exchange Rate Fluctuations
   a. There is a notable fluctuation around 2020, which likely correlates with the COVID-19 pandemic. During this time, many countries faced economic shocks, leading to significant volatility in currency exchange rates.
   b. Following this spike, there is a stabilization trend moving into the later years.
3. Model Performance (Decision Tree Regressor)
   a. Pattern Matching: The Decision Tree Regressor appears capable of capturing major trends in the exchange rate, such as long-term increases and key fluctuations.
   b. Mismatch in Certain Areas: In some segments, such as sharp spikes or sudden drops, the model seems less accurate. This is due to the nature of the Decision Tree algorithm, which divides data into segments based on specific rules, making it less flexible in capturing extreme changes.
   c. Overall, the predicted red line closely follows the blue dots, indicating that the model performs well in capturing general trends.

3.4.3. Technical and Economic Analysis

1. Model Accuracy
   a. The model's performance can be quantitatively evaluated using metrics such as Mean Absolute Error (MAE), Mean Squared Error (MSE), or R-squared (R^2). While the graph provides a visual representation of the results, further analysis requires numerical metrics.
   b. From the graph, it is evident that the model performs well for linear or stable trends but struggles with abrupt fluctuations.
2. External Factors Influencing Exchange Rates
   The graph can be used to identify periods of significant fluctuations, such as:
   a. Global Economic Crises: The spike in exchange rates around 2020 likely reflects the impact of the COVID-19 pandemic, which caused the USD to strengthen against other currencies, including the IDR.
   b. Monetary Policies: Changes in interest rates by Bank Indonesia or the U.S. Federal Reserve may influence exchange rates, as seen in the trends.
   c. Domestic Economic Events: Economic instability in Indonesia, such as high inflation, trade deficits, or rising external debt, may lead to IDR depreciation against the USD.
3. Model Application Potential
   a. This graph demonstrates the potential of the Decision Tree Regressor model for real-world applications, such as predicting exchange rates in financial markets.
   b. The model can assist market participants, such as forex traders, investors, or policymakers, in making decisions based on predicted trends.

4. Conclusion

The use of decision trees for predicting USD to IDR exchange rates has shown potential in capturing patterns from historical data and providing relatively accurate predictions. Decision trees, being a non-linear machine learning model, are able to incorporate various factors that might affect the exchange rate, such as past exchange rates, economic indicators, and global financial events. Through the training process, the model identifies key thresholds and interactions between variables, enabling it to predict future exchange rates with a reasonable degree of accuracy. While decision trees may not always outperform more complex models like random forests or neural networks, they offer an intuitive approach that is easy to interpret, which is valuable for practical applications where model transparency is crucial.

http://doi.org/10.26594/register.v8i2.XXX

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
6 (3) March 2024 185-194

However, it is important to note that the prediction of currency exchange rates is inherently challenging due to the volatility and complexity of financial markets. External factors such as geopolitical events, natural disasters, or sudden shifts in global market sentiment can significantly influence exchange rates, which are difficult for any model to predict accurately. In the case of the USD to IDR pair, while decision trees provide a strong baseline model, incorporating additional techniques such as feature engineering, model ensembling, or time-series analysis may improve accuracy and robustness. Despite the limitations, decision trees remain a valuable tool in the broader context of exchange rate forecasting, particularly when combined with other models or used in conjunction with expert judgment.

5. Suggestion

To improve the performance of decision trees in predicting USD to IDR exchange rates, several strategies can be employed to enhance the model's accuracy and robustness. One crucial approach is to integrate a broader range of economic indicators, such as inflation rates, interest rates, GDP growth, and employment figures, which are known to significantly affect exchange rate movements. By incorporating these macroeconomic factors, the decision tree model can gain a more comprehensive understanding of the variables driving currency fluctuations. Additionally, feature engineering plays a pivotal role in improving model performance; creating derived variables, such as moving averages or volatility indices, could capture hidden patterns in the data that the model might otherwise overlook. Furthermore, one potential avenue to boost predictive power is through ensemble methods, such as random forests or gradient boosting, which combine multiple decision trees to reduce overfitting and enhance generalization. This can help address some of the limitations of a single decision tree, such as its tendency to become overly complex or too specific to the training data. Moreover, incorporating time-series analysis techniques, like ARIMA (AutoRegressive Integrated Moving Average) or advanced deep learning models such as Long Short-Term Memory (LSTM) networks, would allow for a better capture of temporal dependencies and long-term trends, which are often prevalent in exchange rate movements. Time-series models are specifically designed to handle the sequential nature of financial data, making them a valuable addition to any forecasting approach. A hybrid approach that combines decision trees with these more specialized models can lead to a more holistic prediction framework. Finally, leveraging real-time data and keeping the model updated with new information as it becomes available can help account for the fast-changing dynamics of global markets. Ultimately, by combining decision trees with complementary models and continuously refining the feature set, more reliable and accurate predictions of exchange rates can be achieved, providing significant value for businesses and financial institutions making critical investment or operational decisions.

Declaration of Competing Interest

We declare that we have no conflict of interest.

References

[1] A. G. Krishna, K. Indrani, B. Ramgopal, dan M. Sriram, "Prognosis on Analyzing Currency Exchange Rates through Decision Node Regression using Machine Learning," International Journal of Innovative Science and Research Technology, vol. 8, no. 5, pp. 39-44, Mei 2023.
[2] G. Pompeu dan J. Rossi, "Real/Dollar Exchange Rate Prediction Combining Machine Learning and Fundamental Models," Inter-American Development Bank, 2022.
[3] H. Bakhsh, "Currency Exchange Rate Prediction using Python," Kaggle, 2021.
[4] A. Siddiqui, "Currency Exchange Rate Prediction with Machine Learning," The Clever Programmer, 2021
[5] L. Li, P.-A. Matt, dan C. Heumann, "Forecasting Foreign Exchange Rates with Regression Networks Tuned by Bayesian Optimization," arXiv preprint arXiv:2204.12914, 2022.
[6] S. K. Ghosh dan S. K. Saha, "Foreign Exchange Prediction using Decision Tree Algorithm: A Machine Learning Approach," ResearchGate, 2023.
[7] D. Alvear, "Using Decision Trees to Predict Conversion Rate," Medium, 2020. S. Ruder, "

ISSN 2460-7258 (online) | ISSN 1978-1520 (print)
6 (3) March 2024 185-194

[8] M. S. Hossain, M. A. Hossain, dan M. S. Rahman, "Forecasting Foreign Currency Exchange Rate using Convolutional Neural Network with Random Forest Regression Layer," International Journal of Advanced Computer Science and Applications, vol. 13, . 2, pp. 581-588, 2022.
[9] A. S. M. Kayes, "Decision Tree Regressor, Explained," Towards Data Science, 2020.
[10] A. S. M. Kayes, "Comparing Exchange Rate Prediction Models," Data Action Lab, 2021.

http://doi.org/10.26594/register.v8i2.XXX