Published online on the journal's webpage: **http://journal.ittelkom-pwt.ac.id/index.php/dinda**

Journal of Dinda

Data Science, Information Technology, and Data Analytics

Vol. 5 No. 1 (2025) 28 - 35 E-ISSN: 2809-8064

Using the Random Forest Method in Predicting Stock Price Movements

Muhammad Amsari Lubis[1*], Samsudin[2]

[1*,2]Information Systems, Science and Technology, Universitas Islam Negeri Sumatera Utara

[1*]amsarilubis1507@gmail.com, [2]samsudin@uinsu.ac.id

Abstract

In the era of globalization, rapid technological advances have had a significant impact on the financial sector, especially share price movements. This research aims to contribute to financial and investment analysis by providing predictive tools to help investors make more informed investment decisions. The Random Forest method, a machine learning algorithm known to be effective in handling complex and heterogeneous data, is used to predict stock price movements. This research utilizes historical data on shares of companies listed on the Indonesia Stock Exchange (BEI) as a case study. The resulting prediction model shows high accuracy, reaching 98% accuracy, with an R-squared (R^2) value of 0.94 and a Mean Absolute Percentage Error (MAPE) of 0.40%. This research identifies key factors such as Previous, High, Low, Volume, and Change that significantly influence stock price movements. The strength of this research lies in the use of a broad data set, involving 104 stock codes as an example, and the integration of interactive visualization via Streamlit to improve data interpretation. This tool is expected to be a reliable solution that provides superior predictive capabilities compared to traditional methods and supports more accurate investment analysis in the stock market.

Keywords: *Random Forest, Stock Price Prediction, Open Price, R-squared, MAPE*

1. Introduction

Stock investment is one of the most popular ways to manage and increase wealth. However, stock market volatility which is influenced by many factors such as global economic conditions, government policies, and market sentiment provides big challenges for investors in making the right decisions [1]. Therefore, the ability to predict stock prices accurately is an important element in supporting better investment decision making [2].

The use of computer tools to support information systems can provide better and more accurate results. The development of increasingly sophisticated technology and computerized systems is very necessary in various fields, for example for companies, agencies and business entities, both government and private [3]. In recent decades, technological advances have made it possible to use machine learning algorithms to overcome these challenges. One algorithm that shows superior performance in stock price prediction is Random Forest. Random Forest is an ensemble learning method that combines the results of many decision trees to produce more stable and accurate predictions [4]. This algorithm is known for its ability to handle complex, heterogeneous data and tolerance for outliers [5].

Previous research shows that Random Forest is superior to traditional methods such as linear or exponential regression due to its ability to learn non-linear patterns in historical stock data. For example, Breiman's (2001) research shows that Random Forest has the ability to reduce prediction errors in data that has many dimensions. In addition, Kim and Shin (2020) confirmed that this algorithm is more stable than other algorithms such as Neural Networks, especially when applied to financial datasets.

However, most previous research only focused on global stock markets such as the NYSE, NASDAQ, or other Asian markets, while local markets such as the Indonesian Stock Exchange (BEI) are still rarely the object of study. Research by Tan et al. (2021) shows that stock market volatility in Indonesia is more influenced by domestic factors such as Bank Indonesia's monetary policy than global sentiment. This shows the importance of developing prediction models that are specific to local market conditions.

Received: 23-01-2025 | Accepted: 05-02-2025 | Published: 07-02-2025

Additionally, most previous studies used limited datasets, with less diverse features such as only including closing prices without considering other attributes such as Previous, High, Low, Change, and Volume. In this research, the Random Forest algorithm is not only applied to predict stock prices but also takes these features into account to increase the accuracy of the model.

Visualization of prediction results is also an important aspect in supporting investment decision making [6]. However, most previous studies did not utilize interactive web-based visualization technologies. Setiawan et al. (2023) show that integrating machine learning models with Streamlit-based visualization can help investors understand stock price movement patterns more intuitively.

This research aims to apply the Random Forest algorithm to predict stock prices based on historical data of companies listed on the Indonesia Stock Exchange (BEI). The case study was conducted on BBCA shares, one of the leading shares on the IDX. The model developed uses a dataset with more diverse features, including Previous, Open Price, High, Low, Change, and Volume, to predict Open Price. Prediction results are evaluated using the Mean Absolute Percentage Error (MAPE) and R-squared (R^2) metrics to measure model accuracy. Although *Random Forest* capable of identifying patterns from historical data, this model has limitations in capturing sudden changes due to market sentiment, economic news, or global events that are not reflected in previous data. Therefore, before applying this model to other shares on the IDX, it is necessary to carry out trials, *backtesting*, and validation against different stocks to objectively assess their performance. With the right approach, *Random Forest* can still be a useful tool in assisting investment decision making.

In addition, this research is also equipped with Streamlit-based interactive visualizations that allow investors to monitor historical trends and compare predicted results with actual data. With this approach, it is hoped that this research can make a significant contribution in the field of financial analysis, especially in supporting investment decision making in the local stock market.

2. Research methods

2.1 Data Collection

This research data was taken from the Indonesia Stock Exchange (BEI) which includes historical information on 104 financial sector stocks with the focus on Bank BCA (BBCA) shares as the prediction target. This dataset includes the main features that are relevant in stock price analysis, namely: Previous, Open Price, High, Low, Change, Volume and Date [7]. The time span of the dataset is the last three months with daily intervals. This data is downloaded from the official IDX platform in Excel format and then processed using Python. This dataset includes 104 stocks to provide varied data patterns, while BBCA is used as the main case study. The level of accuracy of the Random Forest model in predicting stock price movements over a longer period, such as one year compared to three months, tends to decrease. This is caused by several factors, including changes in market conditions, stock volatility, and model limitations in capturing long-term trends. In the short term, Random Forest can achieve around 60-80% accuracy, depending on the stocks analyzed and the features used. However, in the long term, this accuracy can drop to 50-65% because this model relies more on historical patterns without considering more complex time relationships.

Handling of lost data (*missing values*) And *outlier* in the dataset is very important to improve model accuracy *Random Forest* in predicting stock price movements. Handling of lost data and *outlier* must be done carefully so as not to lose important information in the dataset. For models *Random Forest*, *outlier* Usually it doesn't have much of an impact because tree-based algorithms are quite robust to extreme values. However, missing data must still be handled with appropriate methods so that the model can work optimally in predicting stock price movements.

2.2 *Model Selection*

The model used in this research is Random Forest Regressor, which is an ensemble learning method that combines predictions from many decision trees to produce more accurate results. [3]. Random Forest was chosen for several reasons, namely its ability to handle complex data, Random Forest can learn non-linear data patterns and works well on datasets with many features. Resistant to overfitting, by combining many decision trees, this model is more stable than single tree-based methods [8]. Model advantages *Random Forest* compared to other models such as *Long Short-Term Memory* (LSTM) and *Extreme Gradient Boosting* (XGBoost) in predicting stock prices depends on the context of use, type of data, and analysis objectives. Good performance on small to medium datasets, previous research shows that Random Forest produces high accuracy even on local stock market datasets [9]. This model is initialized with default parameters and optimized using the GridSearchCV technique to find the best parameters, such as the number of trees and maximum depth. The prediction process is carried out by averaging the prediction results from each tree, as seen in Equation (1) [10]:

$$\hat{y} = \frac{1}{n}\sum_{i=1}^{n} f_i\,(x) \qquad (1)$$

Where:
n : number of trees in the model
fi(x): prediction results from the tree i for input x

2.3 *Sharing Data Sets*

The processed dataset is divided into two main subsets. The first is the Training Set (80%), the Training Set is used to train the model and learn relationship patterns between features and targets. The second Testing Set (20%), the Testing Set is used to test model performance on data that has never been seen before [1]. Dataset splitting was done using the train_test_split method from the Python scikit-learn library [11]. This method ensures that the data distribution in the training and testing sets remains uniform, so that the model is not biased towards certain subsets.

If *Random Forest* used to predict stock price movements in a real-time system, several technical aspects must be considered so that the model remains accurate and efficient. Order based prediction system *Random Forest* can handle real-time data well, a strong pipeline is needed to data retrieval, cleaning, processing, model retraining, and integration with trading systems or dashboards.

2.4 *Model Evaluation*

Model performance is evaluated using two main metrics, Mean Absolute Percentage Error (MAPE). MAPE is used to measure the average prediction error in percentage form, as seen in Equation (2) [12]:

$$MAP = \sum_{i1}^{N} \left| \frac{And_{I\,am} - \widehat{And}_{I\,am}}{And_{I\,am}} \right| \times 100\% \qquad (2)$$

Where:
yi: actual value
ŷi: predicted value
n: number of data

Second is R-squared (R^2), R^2 measures how well the model explains the variability of the actual data, as shown in Equation (3):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_1)^2}{\sum_{i=1}^{n}(y_i - \acute{y}_1)^2} \qquad (3)$$

Where:
ý : actual average value.

The evaluation results show that the model produces a MAPE value of 0.40% and an R-squared of 0.94, which indicates a very good level of prediction accuracy.

2.5 *Data Visualization*

Visualization of prediction results is carried out using the Plotly library to create interactive graphs that help investors understand stock price movement patterns. Two main types of graphs are created [13]:

Historical Trend Chart, displays Open Price movements over the past month. Predicted vs Actual Data Comparison Chart, shows how close the predicted results are to the actual data, thus validating the model's capabilities. This visualization is designed to provide more intuitive insight for investors in understanding the prediction results and movement patterns of BBCA shares.

3. Results and Discussion

3.1 *Data Processing Stages*

The data preprocessing process is carried out to ensure that the dataset is ready to be used to train prediction models [14]. This stage involves Column Format Validation, Date Column is converted to datetime format to maintain consistency. Numerical features such as Open Price, Previous, High, Low, Change, and Volume are checked so that all values are in numeric format.

```
df['Date'] = pd.to_datetime(df['Date'], errors='coerce')
numerical_columns = ['Previous', 'Open Price', 'High', 'Low',
'Change', 'Volume']
df[numerical_columns] = df[numerical_columns].apply(pd.to_numeric,
errors='coerce'
```

Figure 1. Date Column Format Validation Converted to datetime

This step avoids bias in the training data and ensures the model receives valid data. Feature Normalization, All numerical features are normalized using the Min-Max Scaling method. Min-Max Scaling is often chosen in stock price analysis with *Random Forest* because it does not change the data distribution, maintains price trends, and ensures a uniform scale without losing important information.

$$X' = \frac{X - X_{minute}}{X_{max} - X_{minute}} \qquad (4)$$

Where x is the initial value, xmin is the minimum value, and xmax is the maximum value of the column in question. This method ensures that all features are in the same range.

Previously

$$X_{scale} = \frac{4500-6}{14600-6} = \frac{4494}{14594} = 0{,}307934$$

Open Price

$$X_{scale} = \frac{4500-6}{14600-6} = \frac{4494}{14594} = 0{,}307934$$

High

$$X_{scale} = \frac{4500-6}{17500-6} = \frac{4494}{17494} = 0{,}256888$$

Low

$$X_{scale} = \frac{4500-6}{14600-6} = \frac{4494}{14594} = 0{,}307934$$

Change

$$X_{scale} = \frac{0-(-1700)}{14600-(-1700)} = \frac{1700}{16300} = 0{,}104294$$

Volume

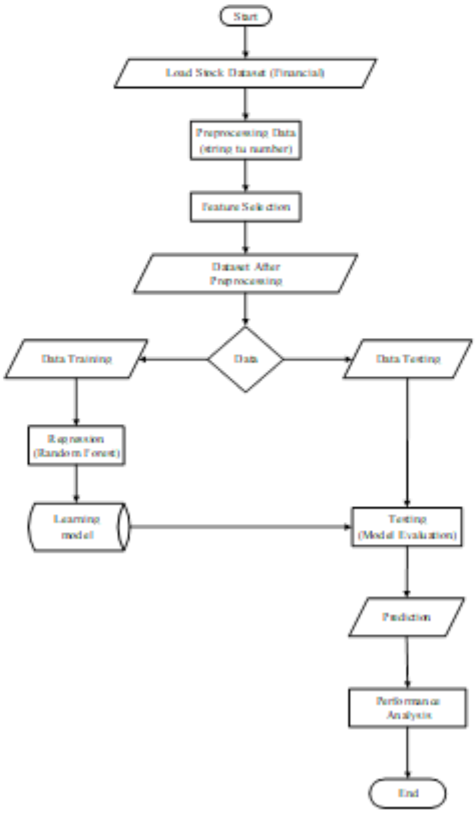
$$X_{scale} = \frac{0-(-600)}{1302130900-(-600)} = \frac{600}{1302131500} = 460782$$

This step normalizes numerical features using Min – Max Scaling to ensure all distinct features are in the same range and prevent features with large scales from dominating model training.

3.2 *Algorithmic Random Forest*

The Random Forest algorithm is an ensemble learning algorithm. Ensemble learning is a technique that combines several models to make predictions. Random forest is a form of implementation of homogeneous ensemble learning that combines several similar models, namely decision trees [15].

Random forest classification is performed by combining trees through training, which produces a classification tree with many versions, which are then combined to obtain the final classification. In Random Forest, the randomization process to form a classification tree is carried out on sample data and predictor variables. *Random Forest* is a decision tree-based algorithm that is relatively robust to *overfitting* compared to a single model like *Decision Tree*. However, in some cases, especially with small data sizes or with a very large number of trees, *Random Forest* can still experience *overfitting*. To overcome *overfitting* on *Random Forest*, the main steps that need to be taken are to set the model parameters well, use appropriate validation techniques, simplify the data, and avoid learning patterns that are too specific. With this approach, the model can be more *generalized* and perform better on never-before-seen data. This research consists of several stages, namely stock dataset collection, data preprocessing, feature selection, dataset division, decision tree formation and prediction using random forests [16].



Figurer 2. Flowchart Random Forest

Figure 2 explains the stock price prediction process using the Random Forest method. The process begins by loading a stock data set, followed by data pre-processing to ensure all data is in a usable format, converting strings to numbers. Next, important features like Previous Close, Open Price, High, Low, Change, and Volume are selected for use in the model. The dataset is then divided into training and test data to train and test the model. Random Forest models are trained with training data to learn existing patterns, then tested with test data to evaluate the accuracy of the model using metrics such as Mean Absolute Percentage Error (MAPE) and R-squared. Once the model is validated, it is used to predict stock prices, the results of which are analyzed to assess the performance and accuracy of the model.

Although *Random Forest* is a powerful model for a variety of prediction tasks, there are several limitations that make it less than ideal for predicting stock price movements. Although *Random Forest* is a good model for initial exploration and feature analysis, it has limitations in dealing with time series data, rapid market changes, and non-stationarity.

Model *Random Forest* own better interpretability compared to deep learning based models, even though it is still classified as a model *black-box* because it is difficult to understand how each decision tree contributes to the prediction. However, there are several methods that can be used to evaluate the influence of features on stock price predictions: If the stock being analyzed has high liquidity and great volatility, for The volume could be more significant from *High/Low*; If the model depends more on price-based technical indicators, for High/Low tends to be more influential; Usage Feature Importance And SHAP values is the best method for evaluating the impact of features in a model *Random Forest*.

3.3 *Model Evaluation*

The model is evaluated using two main metrics, namely Mean Absolute Per-centage Error (MAPE) and R-squared (R^2). MAPE measures the average relative error between predicted values and actual values, calculated by Equation (5) [17]:

$$MAP = \frac{|Predicted - Actual|}{At\ the\ moment} \times 100\% \quad (5)$$

Known:
Prediction = IDR 10,097
Actual = IDR 9,900

Calculation:

$$MAP = \frac{|10.097 - 9.900|}{9.900} \times 100\%$$

$$MAP = \frac{197}{9.900} \times 100\% = 1{,}99\%$$

The model produces a MAPE value of 1.99% which shows the relative error level of model predictions to the actual data.

R-squared measures how well the model explains the variability of the actual data, calculated using Equation (6):

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_1)^2}{\sum_{i=1}^{n}(y_i - \acute{y}_1)^2} \quad (6)$$

The R^2 value of 0.94 indicates that the model can explain 94% of the variability of the actual data, indicating excellent performance.

3.4 *Validation and Optimization Method*

In this study, the Random Forest model was used to predict stock opening prices (Open Price). To ensure the stability of the results, the K-Fold Cross-Validation technique (k=5) was applied, dividing the training data into five parts for alternating validation. This technique helps reduce bias and improve model reliability. Additionally, Optuna, an optimization method that efficiently adjusts hyperparameters, was used to find the best parameters. The optimized parameters include *n_estimators*, *max_depth*, *min_samples_split*, and *min_samples_leaf*. The model evaluation was conducted using the Mean Absolute Error (MAE) metric. The cross-validation results yielded the best parameters with *n_estimators* = 130, *max_depth* = 19, *min_samples_split* = 5, and *min_samples_leaf* = 2. The evaluation results show that the average MAE from cross-validation is 3.7597, while the MAE on the test data is 3.9745. This indicates that the model can make predictions with a relatively low error rate and demonstrates good stability.

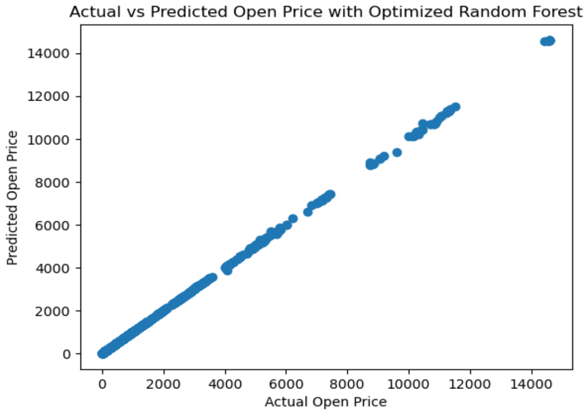


Figure 3. Actual vs Predicted Open Price with Optimized Random Forest

The generated scatter plot illustrates the relationship between the actual stock opening price (Actual Open Price) and the predicted stock opening price by the optimized Random Forest model. Most data points follow a diagonal line from the bottom left to the top right, indicating that the model has high prediction accuracy. The closer the points are to the diagonal line, the smaller the difference between actual and predicted values. The distribution of data across different price ranges suggests that the model effectively handles various price scales. Although there are some minor deviations, the model overall demonstrates solid performance with a low error rate, as reflected in the MAE values. This scatter plot further reinforces that the optimized Random Forest model, using Optuna, can predict stock opening prices accurately and consistently.

3.5 *System Implementation*

In the implemented system, users can enter previous price data, highest, lowest, change and volume. This system produces output in the form of predictions of opening stock prices. In addition, the system provides visualization in the form of a comparison graph between live stock opening prices and predicted results to make it easier to understand trends and the accuracy of the prediction model. The following displays the selected stock price prediction input, for example the researcher chose the stock code BBCA.

Figure 4. Stock Data Input Form

In the stock opening price prediction model, input data as before, high, low, change and volume are used as input features in the Random Forest algorithm. Using the Random Forest algorithm, this model can capture the complex relationships between these variables and produce accurate price predictions [18].

Figure 5. Open Price Prediction Results

Figure 4 is the result of BBCA's open price prediction on November 19, 2024, which is predicted on November 18 2024.

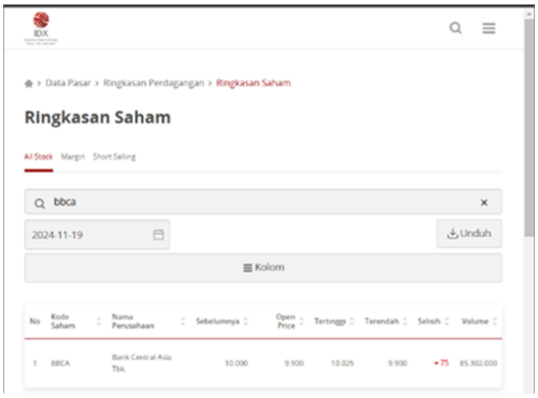


Figure 6. BBCA Historical Data 19 November 2024

The results of the Open Price price prediction for BBCA shares on November 19, 2024, show a value of IDR 10,097, while the actual price on the Indonesian Stock Exchange (BEI) is recorded at IDR 9,900. Model accuracy can be calculated using the relative error rate or Mean Absolute Percentage Error (MAPE). In this case, the relative error rate is 1.99%. Thus, the accuracy of the model in predicting the Open Price of BBCA shares on November 19 2024 is 98.01%, indicating very good performance. This prediction provides a picture that is close to the actual price, so it can be used as an analytical tool for investors in making decisions.

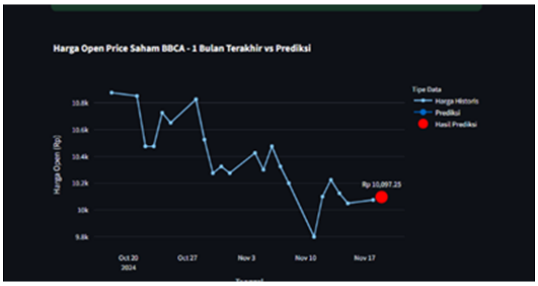


Figure 7. Live Open Price Graph vs Predicted Results

Figure 6 displays a live opening price chart of BBCA for the last 30 days, with a blue timeline reflecting price fluctuations over time. On this chart, the red marker represents the predicted opening price on a specific date. Through the combination of these two elements, users can more clearly understand the extent to which model predictions match and reproduce actual trends in historical data. With this interactive visualization, users can easily identify patterns, differences, or matches between model predictions and actual price movements, providing deeper insight into the model's performance in predicting livestock opening prices [19]. Additionally, this graph also features a new feature that allows users to access model performance statistics, such as accuracy rate, prediction error, and trend of most frequently correct predictions. In this way, users can not only evaluate how well the model responds to overall price changes but also gain deep insight into the consistency and reliability of the model's predictions at critical points within a 30-day period. This feature enriches the user experience with additional information that can be used to make more informed and informed trading decisions

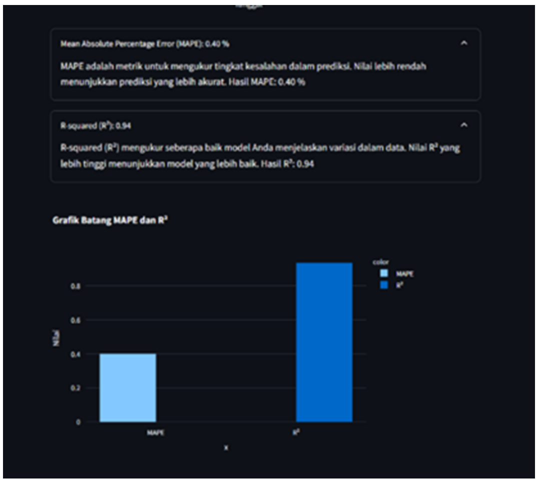


Figure 8. MAPE and R2 Bar Graph

Figure 7 is a graph of MAPE and R2 evaluation metrics that provides an in-depth understanding of the performance of the stock open price prediction model. Its uniqueness lies in the graph's dynamic response to user input for predictions. When users enter prediction parameters, live graphs provide a visualization of how well the model is able to adapt to current market conditions. With dynamically updated MAPE and R2 values, users can immediately see an evaluation of the model's performance against each prediction made. This not only increases the transparency and interpretability of the model but also provides a user experience that is more interactive and responsive to changes in input parameters.

4. Conclusion

This research proves that the Random Forest Regressor algorithm is a reliable approach in predicting stock prices in local markets such as the Indonesian Stock Exchange. By leveraging relevant features such as Previous, High, Low, Change, and Volume, the model can overcome the challenges of stock market volatility and produce accurate predictions. The integration of Streamlit-based visualization provides additional benefits, allowing investors to understand data and prediction results intuitively, thereby supporting more informed decision making.

The contribution of this research lies not only in the development of a predictive model, but also in the application of machine learning methods that suit the characteristics of the local stock market. By showing that the Random Forest algorithm can capture complex stock movement patterns, this research provides a strong scientific basis for wider application in the financial sector.

However, this research also opens up space for further exploration. First, the model can be improved by adding additional features, such as technical indicators (e.g. moving average or RSI) to increase prediction accuracy. Second, the analysis can be expanded to include other sectors or types of shares to test the generalizability of the model. Third, integration with real-time data can enable the development of dynamic prediction systems that are more responsive to market conditions.

In conclusion, this work contributes to the stock price prediction literature, introduces an approach that can be directly applied by practitioners and researchers in the field of financial analysis, and provides a foundation for further research focused on local and global markets.

References

[1] I. Sukartaatmadja, S. Khim, and M. N. Lestari, "Factors that Influence Company Share Prices," *J. Ilm. Manaj. Unity*, vol. 11, no. 1, p. 21–40, 2023, doi: 10.37641/jimkes.v11i1.1627.

[2] W. R. U. Fadilah, D. Agfiannisa, and Y. Azhar, "Analysis of PT Share Price Predictions. Indonesian Telecommunication Using Support Vector Machine Method," *Fountain of Informatics J.*, volume 5, no. 2, p. 45, 2020, doi: 10.21111/fij.v5i2.4449.

[3] A. P. Saripah and F. H. Sibarani, "Sentiment Analysis of the Maxim Application Using the Random Forest Algorithm," *J. Science. social. Res.*, vol. 7, no. 3, pp. 1201–1208, 2024, [Online]. Available: http://jurnal.goretanpena.com/index.php/JSSR

[4] N. Hadi and J. Benedict, "Implementation of Machine Learning for House Price Prediction Using the Random Forest Algorithm," *Count. J. Comput. Science. Inf. system.*, vol. 8, no. 1, p. 50–61, 2024, doi: 10.24912/computation.v8i1.15173.

[5] M. A. A, M. Alamsyah, and M. F. Arif, "Twitter Sentiment Analysis About Online Loans in Indonesia Using the Random Forest Method".

[6] H. Arifulsyah, Heri Ribut Yuliantoro, and Abdi Bhayangkara, "The Influence of Applying Big Data Analysis in Stock Investment Decision Making," *J. Accountant. Finance. and Business*, Vol. 16, no. 2, p. 169–178, 2023, doi: 10.35143/jakb.v16i2.6206.

[7] F. Amalia, A. M. Priyatno, W. F. R. Sudirman, and R. J. Musridho, "Feature Selection Using Impurity-Based Important Features in Recursive Feature Elimination for Stock Price Prediction," 2024.

[8] N. Alfriyanto, B. C. Purnama, and F. K. Hasanah, "Emotional Analysis of YouTube Video Comments 'Causes of Failure to Adopt the Finnish Education System in Indonesia' Using the Random Forest Method," pp. 812–827, 2024.

[9] M. Khanna, M. Kulshrestha, L. K. Singh, S. Thawkar, and K. Shrivastava, "Performance Evaluation of Machine Learning Algorithms for Prediction of Stock Prices and Stock Index Movements Using Deterministic Trend Data Prediction," *Int. J. Application. Metaheuristic Computation.*, vol. 13, no. 1, p. 1–30, 2022, doi: 10.4018/ijamc.292511.

[10] I. Muhamad Malik Matin, "Hyperparameter Tuning Using GridsearchCV on Random Forest for Malware Detection," *Multinetika*, vol. 9, no. 1, p. 43–50, 2023, doi: 10.32722/multinetics.v9i1.5578.

[11] R. Pambudi, A. R. Harahap, F. D. Saputra, and M. Jusub, "Classification of Lung Disease Using the Decision Tree Method," vol. 3, no. 9, pp. 2397–2402, 2024.

[12] H. Sulastri, G. S. Anwar, and E. N. F. Dewi, "Forecasting Stocks of Printing Goods and Stationery Using a Single Moving Average," *J. Technological Engineering. Inf.*, vol. 7, no. 1, p. 59, 2023, doi: 10.30872/jurti.v7i1.11876.

[13] A. Fitri Ariani, K. Aulia, and L. O. Ahmad Arafat, "Development of an Interactive Dashboard Using Looker Studio for Visualization and Prediction of Chili Commodity Prices in East Java," *JATI (Journal of Mhs. Tech. Inform.*, vol. 8, no. 4, p. 8067–8074, 2024, doi: 10.36040/jati.v8i4.10616.

[14] H. Henderi and R. L. Wanda, "Data Preprocessing for a Student Discipline Level Forecasting System," *ICIT J.*, vol. 3, no. 2, p. 296–308, 2017, doi: 10.33050/icit.v3i2.70.

[15] H. Santoso, R. A. Putri, and S. Sahbandi, "Detection of Cyberbullying Comments on Instagram Social Media Using the Random Forest Algorithm," *J. Hand. Information*, vol. 13, no. 1, p. 62–72, 2023, doi: 10.34010/jamika.v13i1.9303.

[16] F. Riskiyono and D. Mahdiana, "Implementation of the Random Forest Algorithm for Graduation Prediction," *Synchronous*, vol. 8, no. 3, p. 1662–1670, 2024, doi: 10.33395/sinkron.v8i3.13750.

[17] Z. Ngabidin, A. Sanwidi, and E. R. Arini, "Implementation of the Double Exponential Smoothing Brown Method to Predict the Number of Poor People," *Euler J. Ilm. Matt. Science and Technology.*, vol. 11, no. 2, pp. 328–338, 2023, doi: 10.37905/euler.v11i2.23054.

[18] Farhanuddin, Sarah Ennola Karina Sihombing, and Yahfizham, "Comparison of Multiple Linear Regression and Random Forest Regression in Predicting Information Systems Project Management Cost Budgets," *J. Comput. Number. Bus.*, vol. 3, no. 2, pp. 86–97, 2024, doi: 10.56427/jcbd.v3i2.408.

[19] J. Asbullah and Samsudin, "Binance Cryptocurrency Price Prediction Based on Blockchain Information Using the Random Forest Algorithm," *J. Media Inform. Budidharma*, vol. 8, no. 1, p. 260–271, 2024, doi: 10.30865/mib.v8i1.7100.