



A Comparative Analysis of XGBoost and Random Forest for Time Series Based Stock Price Prediction with Directional Movement Evaluation

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Abstract—Stock price prediction remains a complex task due to the dynamic nature of financial time series and the difficulty of extracting informative patterns from historical price movements. This study addresses the need to better understand whether the choice of model or the design of time series features plays a more dominant role in prediction performance. The objective of this research is to comparatively evaluate Extreme Gradient Boosting (XGBoost) and Random Forest for stock price prediction using engineered time series features, while also assessing their ability to capture directional price movements. The proposed approach applies a structured pipeline involving data preprocessing, extraction of time series features (lag, moving average, and volatility), and evaluation using a time-aware data split to preserve temporal order. Unlike conventional studies that focus solely on prediction accuracy, this research integrates both regression-based evaluation (RMSE, MAE, and R^2) and directional movement analysis using confusion matrix, along with feature importance interpretation to understand model behavior. The experimental results, based on 1,258 daily stock price records, show that XGBoost achieved an RMSE of 457.97, MAE of 345.28, and R^2 of 0.884, while Random Forest obtained an RMSE of 462.01, MAE of 351.02, and R^2 of 0.882. The difference in R^2 (0.002 or 0.2%) indicates that both models perform comparably, with no substantial performance gap. Directional evaluation further reveals that both models are more accurate in predicting upward trends than downward movements. These findings suggest that feature engineering plays a more critical role than model selection in this context, providing a practical contribution to the development of stock prediction systems.

Keywords: Stock Price Prediction; XGBoost; Random Forest; Time Series; Yahoo Finance

1. INTRODUCTION

The capital market is one of the important sectors in the economy that acts as a means of raising funds and investment. Stocks, as the main instrument in the capital market, have price characteristics that fluctuate and are influenced by various factors, both internal and external factors, such as macroeconomic conditions, monetary policy, and market sentiment (Bettahi et al., 2025). High stock price fluctuations cause investment risks to increase and make it difficult for investors to make optimal decisions. Therefore, stock price prediction is an important problem that continues to be studied in the fields of finance and information technology. Stock price data is a time series, where the price value at one time is influenced by the historical value in the previous period. In addition, stock data also contains non-linear patterns and high volatility (Vuong et al., 2022). Conventional approaches, such as simple technical analysis and classical statistical methods, often have limitations in capturing such complexity. These models generally rely on assumptions of linearity and data stationarity, making them less flexible when applied to dynamic and volatile stock data.

The development of machine learning offers a more adaptive alternative approach to modeling financial data. Machine learning algorithms are able to learn nonlinear relationships and complex patterns without requiring strict data distribution assumptions (Ferrouhi & Bouabdallaoui, 2024). Some studies in the last five years have shown that ensemble learning based methods perform better than traditional statistical methods in predicting stock prices (Vuong et al., 2022). The ensemble approach combines multiple models to improve the accuracy and stability of predictions. Extreme Gradient Boosting (XGBoost) is one of the boosting-based ensemble algorithms that is widely used in stock price prediction. Previous research reported that XGBoost can provide competitive prediction results because it has an effective gradient optimization and regularization mechanism in reducing overfitting (Lina et al., 2026). On the other hand, Random Forest, as a bagging-based ensemble algorithm, is also widely used because it is stable to noise and able to handle high-dimensional data.

In recent years, the development of machine learning has opened up new opportunities in stock price modeling and prediction. Machine learning algorithms are able to learn non-linear patterns and complex relationships between variables without requiring strict data distribution assumptions. Research by (B, 2023) shows that the ensemble learning approach is able to provide better prediction results than traditional statistical methods on volatile stock data. Furthermore, (Yun et al., 2021) report that the Extreme Gradient Boosting (XGBoost) algorithm has superior performance in stock price prediction due to its ability to incorporate multiple decision tree models gradually through a boosting mechanism.

Another study by (Mostafavi & Hooman, 2025) utilized the Random Forest algorithm for stock price prediction and showed that this method is quite stable in dealing with data noise and is able to produce consistent predictions. Random Forest works with a bagging approach, where multiple decision trees are trained in parallel, and the results are combined to reduce model variance. In addition, (Mostafavi & Hooman, 2025) integrates time series features such as lag features and moving averages with decision tree-based algorithms and reports an improvement in prediction performance compared to the use of raw price data without feature extraction. Recent research by (Kulkarni et al., 2025) also emphasizes the importance of historical trend-based features in improving the performance of stock price

prediction models. Several studies report that Random Forest provides consistent performance in predicting stock prices, especially on high-fluctuating data. Although both algorithms have been widely used, the literature review shows that most studies still focus on applying one particular algorithm or using different feature configurations, making performance comparisons less objective. In addition, the evaluations carried out generally only focus on the accuracy of predicting the value of stock prices, without examining the model's ability to predict the direction of price movements. In fact, information on the direction of rising or falling stock prices is an important aspect in investment decision-making. Based on these problems, there is a research gap that needs to be studied further, namely the need to compare the performance of the XGBoost and Random Forest algorithms using the same dataset and time series features, as well as a more comprehensive evaluation.

This study proposes the use of time series features in the form of lag features, moving averages, and volatility to capture historical patterns and trends of stock price movements in a more representative manner. By using identical features, a comparison of the performance of the two algorithms can be done fairly and objectively. The purpose of this study is to compare the performance of the Extreme Gradient Boosting (XGBoost) and Random Forest algorithms in predicting stock prices based on the time series feature. The evaluation was carried out using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and determination coefficient (R^2) metrics, as well as additional evaluation in the form of a confusion matrix in the direction of stock price movements (Liu et al., 2022). The dataset used is historical daily stock price data from Yahoo Finance, which is public and reproducible. The urgency of this research lies in the need for a stock price prediction model that is not only numerically accurate but also informative in describing the direction of price movements. The results of this study are expected to make a practical contribution as a reference in the selection of stock price prediction algorithms, as well as academic contributions in enriching empirical studies on the application of ensemble learning algorithms to financial time series data. The main contribution of this study is to present a comparison of the performance of XGBoost and Random Forest on the same dataset and time series features, to integrate the evaluation of price value prediction and the direction of stock price movements, and to provide empirical evidence on a more effective algorithm in the context of stock price prediction based on the time series features. Thus, this study represents a state-of-the-art approach in modeling stock price predictions based on machine learning that is efficient and easy to implement.

2. RESEARCH METHODOLOGY

This study uses a quantitative approach by applying *a machine learning* method to compare the performance of the Extreme Gradient Boosting (XGBoost) and Random Forest algorithms in predicting stock prices based on the time series feature. The research process is carried out systematically through several stages, including the collection of historical stock price data from Yahoo Finance, pre-processing of data, extraction of time series features, sharing of training data and time series-based test data, model training, and model performance evaluation (Nugroho et al., 2025). The evaluation was carried out using the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and determination coefficient (R^2) metrics, as well as analysis of the direction of stock price movements using a confusion matrix (Noorunnahar et al., 2023). This approach is designed to obtain an objective and comprehensive performance comparison between the two algorithms on the same dataset and feature configuration. The research method can be seen in Figure 1.

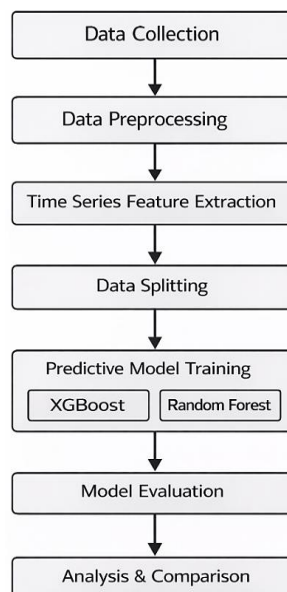


Figure 1. Research Stages



2.2 Data Collection

The data collection stage was carried out using a historical stock price dataset sourced from Yahoo Finance, which was taken from Kaggle, with a total of 1258 data points. This dataset contains daily stock price data consisting of the attributes of transaction date (Date), opening price (Open), highest price (High), lowest price (Low), closing price (Close or Adj Close), and transaction volume. The data used is a time series, so each observation has a dependence on time. This dataset was chosen because it is open, easy to reproduce, and widely used in stock price prediction research.

2.3 Pre Data Processing

In the pre-processing stage, the process of cleaning and preparing the data is carried out before being used in modeling. The steps taken include converting date attributes to datetime format, sorting data based on time, handling missing values, and selecting target variables. The closing price variable (Close) is used as a target because it represents the final value of the stock on each trading day and is commonly used in stock price prediction analysis. This stage aims to ensure the data is in a consistent condition and ready for feature extraction (Ritonga et al., 2024)

2.4 Time Series Feature Extraction

Feature extraction is done to capture temporal patterns that cannot be represented by a single price value. The time series features used include lag features (lag-1, lag-5, and lag-10) to represent the price effect on the previous day, moving averages (MA-5 and MA-10) to identify short- and medium-term trends, and volatility calculated using the standard deviation of closing prices within a given time window. These features are designed to help models learn historical patterns of stock price movements (Assaduddiari et al., 2025).

2.5 Data Sharing

The data that has been extracted is then divided into training data and testing data, with a proportion of 80% training data and 20% test data. The division is carried out sequentially based on time (time series split) to avoid data leakage (data leakage). With this approach, the model is only trained using past data and tested using data in subsequent periods, so that the resulting evaluation is more realistic (Nabilah Selayanti et al., 2025)

2.6 Prediction Model Training

At this stage, training was carried out on two machine learning algorithms, namely Extreme Gradient Boosting (XGBoost) and Random Forest Regression. Both algorithms were trained using the same training data and identical time series features to make the performance comparison fair. XGBoost was chosen for its ability to handle non-linearity and has a boosting mechanism, while Random Forest is used as a stable and commonly used bagging-based comparison model as a baseline (Gono et al., 2023)

2.7 Model Evaluation

Model evaluation was carried out using test data with Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and coefficient of determination (R^2) metrics to measure the accuracy of numerical predictions. In addition, an additional evaluation was carried out using the confusion matrix in the direction of price movements (up/down) to assess the model's ability to predict the direction of stock price trends. This evaluation provides a quantitative and qualitative overview of the performance of each algorithm (Hossain & Kaur, 2024)(Yang, 2023).

2.8 Analysis of Comparative Results

The final stage is to compare the performance of XGBoost and Random Forest based on the results of evaluation metrics and prediction visualization. This comparison is used to determine algorithms that have better performance in predicting stock prices based on time series features, as well as to analyze the advantages and limitations of each method (Yi, 2023).

3. RESULT AND DISCUSSION

3.1 Result

The results of the model test conducted at the evaluation stage using test data obtained a comparison of the performance between the Extreme Gradient Boosting (XGBoost) and Random Forest algorithms in predicting stock prices based on the time series feature. The test was carried out with a time series split-based data sharing scheme, where 80% of the data was used as training data and 20% of the data was used as test data, so that the model only studied patterns from historical data and was evaluated on the data of the next period. This approach is used to avoid data *leakage* and ensure that the test results represent realistic predictive conditions. The results of the evaluation showed that the XGBoost algorithm produced an RMSE value of 457.97, MAE of 345.28, and a coefficient of determination (R^2) of 0.884, while the Random Forest algorithm obtained an RMSE value of 462.01, MAE of 351.02, and R^2 of 0.882. The lower RMSE and MAE values on XGBoost indicate that the average prediction error generated is smaller than that of Random Forest. In addition, a higher R^2 value indicates that XGBoost can better explain the variation in stock price data. This difference

in results shows that the boosting mechanism in XGBoost is more effective in studying historical patterns and non-linear relationships in stock price data based on time series features than the bagging approach in Random Forest. Thus, the results of this test support the objectives of the study and confirm that XGBoost has a relatively superior performance in stock price prediction in the dataset used, making it worthy of recommendation in the context of this study.

Table 1. Comparison of XGBoost and Random Forest Results

Metode	RMSE	MAE	R ²
XGBoost	457.966139	345.284469	0.884150
Random Forest	462.006955	351.019988	0.882097

Figure 2, it shows that the confusion matrix of price movement direction for the Extreme Gradient Boosting (XGBoost) algorithm shows the model's ability to classify the direction of stock price movement into two classes, namely up and down, based on the results of price predictions. From the test results, as many as 93 data points with an actual upward direction were correctly predicted as up, while 51 data points with an actual downward direction were correctly predicted as down. However, there are still misclassifications, namely 69 actual data points predicted as rising and 41 actual data points predicted as down. This pattern indicates that the XGBoost model tends to be more sensitive in capturing price increase signals than price declines, which is likely influenced by the dominance of trend-based features such as moving averages and lag features. Nonetheless, XGBoost's ability to classify the overall direction of price movements shows that the model is not only effective in predicting the value of stock prices but also quite informative in identifying the direction of price movements, thus supporting the research objectives in comparing the performance of the time series feature-based stock price prediction algorithm.

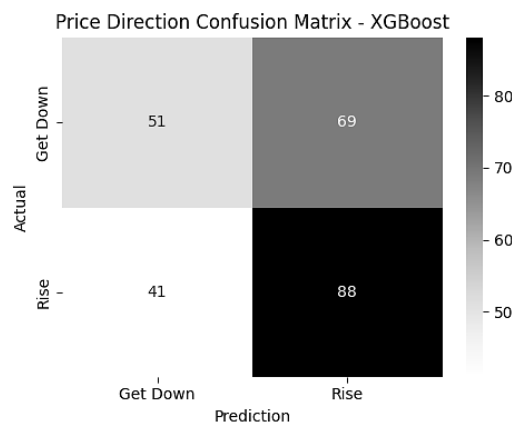


Figure 2. Confusion Matrix XGBoost

Figure 3 showing that the confusion matrix of price movement direction for the Random Forest algorithm shows the model's performance in classifying the direction of stock price movement into up and down classes. Based on the test results, the Random Forest model managed to correctly predict 89 data points with an actual upward direction and 48 data points with an actual downward direction. However, there are still misclassifications, namely 72 actual data points predicted as rising and 38 actual data points predicted as down. These results indicate that Random Forest, similar to XGBoost, tends to be more responsive to bullish patterns than price declines. However, the number of misclassifications in both classes is relatively higher than that of XGBoost, which suggests that Random Forest's consistency in predicting the direction of stock price movements is slightly lower.

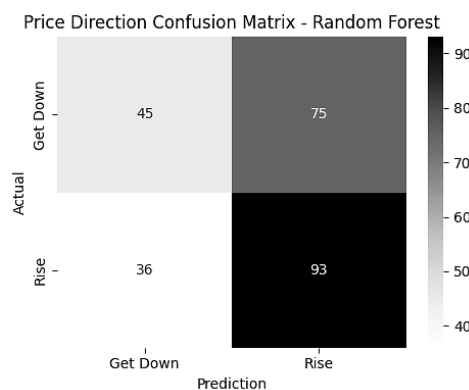


Figure 3. Confusion Matrix Random Forest

Figure 4 showing a comparison of stock price predictions shows that both algorithms, namely XGBoost and Random Forest, were able to follow the general trend pattern of actual stock price movements during the test period. The prediction lines of the two models move relatively in the direction of the actual data, especially in the phases of rising and falling prices that occur gradually.

Nevertheless, XGBoost's prediction looks closer to the actual price for most periods, especially when there are quite significant trend changes, while Random Forest tends to produce a smoother prediction curve and lags a little behind in response to sharp price fluctuations. This difference shows that XGBoost has a better ability to capture the dynamics of stock price changes based on the *time series* feature. Overall, the results of this visualization are consistent with the numerical evaluation metrics obtained, where XGBoost showed lower prediction errors than Random Forest, thus strengthening the conclusion that XGBoost is more effective in modeling stock price predictions in this study.

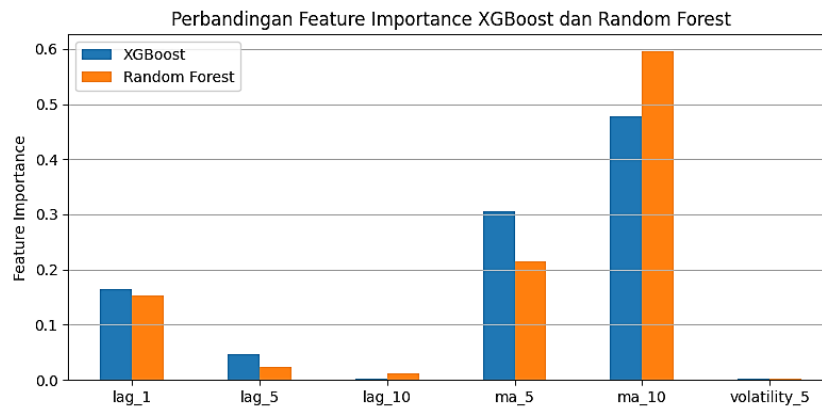


Figure 4. Stock Price Prediction Comparison

A comparison of feature importance between the XGBoost and Random Forest algorithms shows that both models both place trend-based features as the most influential factor in stock price predictions. The 10-day moving average (MA-10) feature has the highest level of importance in both algorithms, with a greater contribution to Random Forest than XGBoost, indicating that medium-term trends are very dominant in determining predictive outcomes. In addition, the 5-day moving average (MA-5) feature also makes a significant contribution, particularly to XGBoost, which suggests that the model is more sensitive to short-term trend changes. The lag-1 feature has a moderate effect on both models, indicating that the stock price one day earlier is still relevant in the prediction process. In contrast, the lag-5, lag-10, and 5-day volatility features have relatively small contributions, so short-term fluctuations and volatility levels are not the main factors in the stock price modeling in this study. Overall, these results confirm that the time series feature-based stock price prediction approach is more influenced by historical trend patterns than by random daily price variations.

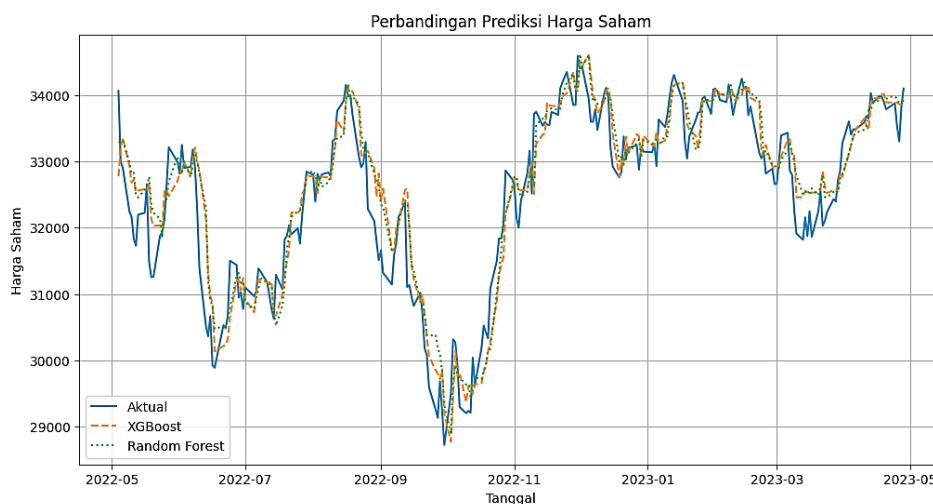


Figure 5. Feature Importance Comparison

3.2 Discussion

Based on the results of the study, the Extreme Gradient Boosting (XGBoost) algorithm has better performance than Random Forest in predicting stock prices based on the time series feature. The hypothesis is based on the characteristics of XGBoost, which uses a boosting mechanism to minimize errors iteratively, so it is expected to be able to model non-linear relationships and historical patterns of stock prices more effectively. Based on the results of the tests that have



been carried out, the hypothesis of this study is acceptable, because XGBoost has consistently shown superior performance to Random Forest in almost all evaluation metrics used. The results of the numerical evaluation showed that XGBoost produced lower RMSE and MAE values and higher R^2 values than Random Forest. These findings indicate that the stock price predictions generated by XGBoost have a smaller error rate and are able to better explain the variations in stock price data. This result is in line with the purpose of the study, which is to obtain an accurate stock price prediction model by utilizing time series features in the form of lag features, moving average, and volatility. In addition, the use of time series split-based data sharing ensures that the model is tested on future data chronologically, so that the evaluation results are realistic and do not experience data leakage.

The confusion matrix analysis of the direction of price movement also shows that XGBoost has a better ability to classify the direction of stock price movements than Random Forest. Although both models tend to be more accurate in predicting the direction of price increases than price declines, XGBoost produces a higher number of correct predictions and lower misclassifications. This shows that the model is not only excellent at predicting the value of stock prices but also quite informative at identifying the direction of price movements, which is an important aspect of investment decision-making. The results of the visualization of stock price predictions strengthen the findings of the numerical evaluation and confusion matrix. XGBoost's prediction curve looks closer to the actual price and is more responsive to trend changes than Random Forest, which tends to produce smoother predictions and lag a bit when there are quite sharp price changes. These findings show that the boosting approach on XGBoost is more effective in capturing the dynamics of stock price changes based on the time series feature.

The findings of this study are consistent with the results of previous research. (B, 2023) reported that the boosting-based ensemble learning method provides better performance than the traditional method in stock price prediction. (Gono et al., 2023) also showed that XGBoost excels at modeling stock data that is non-linear and volatile. On the other hand, the results of this study are also in line with (Sharma et al., 2023), which states that Random Forest has stable performance, but tends to be less sensitive to rapid changes in price patterns. The research (Dehvari et al., 2025) confirms that the use of time series features such as moving averages and lag features contributes significantly to improving model performance, which is also proven in this study through feature importance analysis. The main difference between this study and the previous study lies in the direct comparison of XGBoost and Random Forest using identical time-series datasets and features, as well as an evaluation that focuses not only on price value prediction, but also on the direction of stock price movements. Thus, this study makes a new contribution in the form of a more comprehensive and objective comparative analysis of two popular ensemble learning algorithms.

4. CONCLUSION

Based on the results of the research that has been conducted, it can be concluded that the purpose of the study, to compare the performance of the Extreme Gradient Boosting (XGBoost) and Random Forest algorithms in predicting stock prices based on the time series feature, has been well achieved. The test results showed that both algorithms were able to model historical stock price patterns, but XGBoost performed better than Random Forest. This is evidenced by lower Root Mean Square Error (RMSE) and Mean Absolute Error (MAE) values, as well as higher determination coefficient (R^2) values. Quantitatively, XGBoost can explain about 88.4% of the variation in stock price data, while Random Forest explains about 88.2%, which shows that XGBoost has slightly better predictive capabilities. In addition, evaluation using the confusion matrix of price movement shows that XGBoost has a more consistent level of directional prediction accuracy than Random Forest, especially in identifying upward price movements, thus providing more relevant information for investment decision-making. Thus, the research problem related to the selection of algorithms that are more effective in predicting stock prices can be answered, where XGBoost is recommended as a superior model in the context of this research. However, this study has limitations, including the use of datasets from a single source and the application of time series features, which are still limited to lag, moving average, and volatility. Therefore, further research can be developed by adding other technical indicators, fundamental data, or market sentiment, as well as testing models on different stocks and time periods to improve the generalization and accuracy of the prediction model.

REFERENCES

- Assaduddiari, I. G., Kurdhi, N. A., Siri, Z., & Aruchunan, E. (2025). Forecasting Tesla Stock Price Using XGBoost, Random Forest, and CatBoost: A Comparative Study with TreeSHAP Interpretation of the Best Model. *2025 International Conference on Artificial Intelligence and Technological Solutions (ICAITech)*, 309–314. <https://doi.org/10.1109/ICAITech66481.2025.11387624>
- B, Y. Z. (2023). *Stock Price Prediction Method Based on XGboost Algorithm*. Atlantis Press International BV. <https://doi.org/10.2991/978-94-6463-030-5>
- Bettahi, A., Belouadha, F. Z., & Harroud, H. (2025). A Modular and Explainable Machine Learning Pipeline for Student Dropout Prediction in Higher Education. *Algorithms*, 18(10), 1–31. <https://doi.org/10.3390/a18100662>
- Dehvari, M., Farzaneh, S., & Forootan, E. (2025). Forecasting rainfall events based on zenith wet delay time series utilizing eXtreme gradient boosting (XGBoost). *Advances in Space Research*, 75(3), 2584–2598. <https://doi.org/https://doi.org/10.1016/j.asr.2024.11.013>



- Ferrouhi, E. M., & Bouabdallaoui, I. (2024). A comparative study of ensemble learning algorithms for high-frequency trading. *Scientific African*, 24, e02161. <https://doi.org/https://doi.org/10.1016/j.sciaf.2024.e02161>
- Gono, D. N., Napitupulu, H., & Firdaniza. (2023). Silver Price Forecasting Using Extreme Gradient Boosting (XGBoost) Method. *Mathematics*, 11(18). <https://doi.org/10.3390/math11183813>
- Hossain, S., & Kaur, G. (2024). Stock Market Prediction: XGBoost and LSTM Comparative Analysis. *2024 3rd International Conference on Artificial Intelligence For Internet of Things (AIIoT)*, 1–6. <https://doi.org/10.1109/AIIoT58432.2024.10574794>
- Kulkarni, M. S., Vijayakumar Bharathi, S., Perdana, A., & Kilari, D. (2025). A Quest for Context-Specific Stock Price Prediction: A Comparison Between Time Series, Machine Learning and Deep Learning Models. *SN Computer Science*, 6(4), 335. <https://doi.org/10.1007/s42979-025-03848-y>
- Lina, S., Sitio, M., Samudra, Y., Informatika, T., Inggris, S., & Pamulang, U. (2026). *Comparative Analysis Of Bagging And Boosting Models In*. 11(3), 979–986. <https://doi.org/10.33480/jitk.v11i3.7579.COMPARATIVE>
- Liu, J., Zhang, S., & Fan, H. (2022). A two-stage hybrid credit risk prediction model based on XGBoost and graph-based deep neural network. *Expert Systems with Applications*, 195, 116624. <https://doi.org/https://doi.org/10.1016/j.eswa.2022.116624>
- Mostafavi, S. M., & Hooman, A. R. (2025). Key technical indicators for stock market prediction. *Machine Learning with Applications*, 20, 100631. <https://doi.org/https://doi.org/10.1016/j.mlwa.2025.100631>
- Nabilah Selayanti, Dwi Amalia Putri, Trimono Trimono, & Mohammad Idhom. (2025). Prediksi Harga Penutupan Saham Bbri Dengan Model Hybrid Lstm-Xgboost. *Informatika: Jurnal Teknik Informatika Dan Multimedia*, 5(1), 52–64. <https://doi.org/10.51903/informatika.v5i1.1011>
- Noorunnahar, M., Chowdhury, A. H., & Mila, F. A. (2023). A tree based eXtreme Gradient Boosting (XGBoost) machine learning model to forecast the annual rice production in Bangladesh. *PLOS ONE*, 18(3), 1–15. <https://doi.org/10.1371/journal.pone.0283452>
- Nugroho, W. A., Rachman, F. D., Sياهو, B. K., Iswanto, I. A., & Joddy, S. (2025). Hybrid Ensemble Model Approaches for Stock Price Forecasting Using LSTM, Random Forest, ARIMA, and Linear Regression as Meta-Learner. *Procedia Computer Science*, 269, 901–910. <https://doi.org/https://doi.org/10.1016/j.procs.2025.09.033>
- Ritonga, A., Ma, A., & Suwarno, I. (2024). *Stock Price Forecasting with Multivariate Time Series Long Short-Term Memory : A Deep Learning Approach*. 5(5), 1322–1335. <https://doi.org/10.18196/jrc.v5i5.22460>
- Sharma, A. K., Li, L. H., & Ahmad, R. (2023). Default Risk Prediction Using Random Forest and XGBoosting Classifier. In *Smart Innovation, Systems and Technologies* (Vol. 314). Springer International Publishing. https://doi.org/10.1007/978-3-031-05491-4_10
- Vuong, P. H., Dat, T. T., Mai, T. K., Uyen, P. H., & Bao, P. T. (2022). *Stock-Price Forecasting Based on XGBoost and LSTM*. <https://doi.org/10.32604/csse.2022.017685>
- Yang, T. (2023). Sales Prediction of Walmart Sales Based on OLS, Random Forest, and XGBoost Models. *Highlights in Science, Engineering and Technology*, 49. <https://doi.org/10.54097/hset.v49i.8513>
- Yi, S. (2023). Walmart Sales Prediction Based on Machine Learning. *Highlights in Science, Engineering and Technology*, 47. <https://doi.org/10.54097/hset.v47i.8170>
- Yun, K. K., Yoon, S. W., & Won, D. (2021). Prediction of stock price direction using a hybrid GA-XGBoost algorithm with a three-stage feature engineering process. *Expert Systems with Applications*, 186, 115716. <https://doi.org/https://doi.org/10.1016/j.eswa.2021.115716>