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Comparative Analysis of ARIMA and XGBoost Models for Forecasting

Muhammad Alif Nugraha Diaz[1*], Noper Ardi[2*]
* Informatics Engineering, Batam State Polytechnic
** Software Engineering Technology, Batam State Polytechnic
Nugraha.alif17@gmail.com[1], noperardi@polibatam.ac.id[2]

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ABSTRACT

The blue-chip banking sector in Indonesia, including BBCA, BBRI, and BBNI, exhibits high volatility and non-linear movements, presenting significant challenges for investors in mitigating financial risk. This study aims to develop and comparatively evaluate the performance of the traditional statistical model, Autoregressive Integrated Moving Average (ARIMA), against the modern machine learning algorithm, Extreme Gradient Boosting (XGBoost), in predicting daily closing stock prices for a one-day horizon (H+1). The research methodology employs a Research and Development (R&D) approach, utilizing historical data for model training and validation. The results demonstrate that the XGBoost model consistently outperforms ARIMA across all tested samples. Specifically, XGBoost achieved a Mean Absolute Percentage Error (MAPE) of **0.55%** for BBCA, **1.10%** for BBRI, and **0.88%** for BBNI, which is significantly lower than ARIMA's MAPE range of **1.48%** to **1.60%**. The study concludes that ensemble learning models are more effective at capturing non-linear volatility patterns in the Indonesian capital market and serve as a more reliable decision support tool for investors.

I. INTRODUCTION

The capital market serves as a vital pillar of the Indonesian economy, acting as both an efficient mechanism for capital allocation and a definitive barometer for national economic health. Within the Indonesia Stock Exchange (IDX), the commercial banking sector exerts a disproportionately massive influence on the movement of the Indonesia Composite Index (IHSG). Among the financial institutions listed on the exchange, three banking giants stand out as the primary anchors of market capitalization and systemic stability, namely Bank Central Asia (BBCA), Bank Rakyat Indonesia (BBRI), and Bank Negara Indonesia (BBNI). Combined, these institutions represent a substantial weight in the IHSG calculation, meaning that any microeconomic fluctuations within these banks or macroeconomic policy shifts by Bank Indonesia trigger immediate, amplified ripple effects across the entire capital market. Consequently, because of their high liquidity and strong financial fundamentals, these blue-chip stocks have become the default targets for domestic institutional investors, retail traders, and foreign fund managers seeking sustainable capital gains.

Despite their status as secure, long-term investments, navigating the daily price trajectories of BBCA, BBRI, and BBNI presents a formidable challenge for market participants. Modern financial markets operate under highly complex, dynamic, and non-linear regimes where asset prices are continuously bombarded by an array of endogenous and exogenous factors. These include global macroeconomic shocks, interest rate adjustments, fluctuations in foreign capital flows, and shifting market sentiments driven by behavioral biases and high-frequency noise trading. As a result, the time-series data generated by these premier banking stocks is inherently chaotic, exhibiting non-stationarity, high volatility clustering, and significant noise. For risk managers and short-term tactical traders alike, this high degree of volatility and asymmetry often obscures the underlying market trends, rendering traditional, intuitive decision-making highly susceptible to error and capital loss.

To mitigate these risks and extract predictive signals from market noise, quantitative forecasting has historically relied on traditional econometric frameworks. The Autoregressive Integrated Moving Average (ARIMA) model, rooted in the classic Box-Jenkins methodology, has long been the standard for linear time-series forecasting due to its mathematical

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rigor, simplicity, and strong statistical interpretability when capturing linear dependencies. However, its rigid mathematical structure requires data stationarity and struggles significantly when confronted with the structural breaks, sudden market shocks, and asymmetric fluctuations characteristic of modern emerging markets. In response to these linear limitations, the paradigm of financial forecasting has increasingly shifted toward advanced machine learning algorithms. Extreme Gradient Boosting (XGBoost) offers a robust alternative by utilizing an ensemble of weak decision trees and integrating a regularized objective function, which allows it to inherently excel at mapping intricate, multi-dimensional, and non-linear relationships without requiring strict distributional assumptions.

While classical statistical models offer strong baseline interpretability, they lack the flexibility to adapt to sudden market fluctuations, whereas advanced machine learning models possess immense predictive power but require precise empirical validation within specific market contexts. This research addresses this critical gap by providing a direct, empirical comparative evaluation between the traditional ARIMA framework and the advanced XGBoost algorithm to determine the most effective approach for predicting prices on an H+1 horizon. This short-term forecasting horizon is chosen intentionally as it provides the most actionable insights for active portfolio rebalancing and short-term risk management within Southeast Asia's largest economy. By systematically benchmarking both models using standard performance metrics such as Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE), this study aims to determine whether the non-linear capabilities of XGBoost definitively outperform the linear baseline of ARIMA, thereby offering valuable empirical insights and practical tools for financial practitioners and algorithmic traders operating in the Indonesian context.

II. METHODOLOGY

This study adopts the Research and Development (R&D) methodology, encompassing requirement analysis, planning, development, testing, and evaluation.

A. ARIMA Model

Autoregressive Integrated Moving Average (ARIMA) is a statistical model designed for linear time series data. The model consists of three primary components: **AR(p)**, which regresses current values against past observations; **I(d)**, which achieves data stationarity through differencing; and **MA(q)**, which incorporates past prediction errors.

- **AR(p)**: Autoregressive component, where the current value depends on past values:

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \cdots + \phi_p Y_{t-p} + \epsilon_t$$

- **I(d)**: Integrated component, using differencing to achieve stationarity.
- **MA(q)**: Moving Average component, modeling current values as a function of past prediction errors:

$$Y_t = \mu + \epsilon_t + \theta_1 \epsilon_{t-1} + \cdots + \theta_q \epsilon_{t-q}$$

B. XGBoost Model

XGBoost is a decision-tree-based ensemble learning algorithm that constructs a robust predictive model by sequentially combining multiple weak learners. In this study, the time-series data is transformed into a supervised learning format by utilizing lag values as input features.

$$\widehat{C_t} = \sum (k = 1)^K f_k(x_t)\,, f_k \in F$$

Where $\widehat{C_t}$ is the predicted closing price and x_t represents the vector of lag values (Lag 1 to Lag 5).

C. Research Procedure

1. Data Collection: Daily closing price data were downloaded via the Yahoo Finance API using the yfinance library.
2. Data Preprocessing: Data was cleaned of missing values using forward fill or drop methods. For ARIMA, stationarity was ensured via First-Order Differencing $\Delta Y_t = Y_t - Y_{t-1}$ based on Augmented Dickey-Fuller (ADF) tests
3. Model Development: The optimal parameters (p, d, q) for the ARIMA model were determined through a Grid Search based on the lowest AIC (Akaike Information Criterion) value. Meanwhile, the XGBoost model training was conducted using a configuration of 100 trees (estimators) and a maximum depth of 5.
4. Experimental Setup: Models were implemented in Python (Google Colab). Hardware included a Ryzen 5 5600 processor and 16 GB RAM.

D. Evaluation Metrics

The forecasting performance of both models was evaluated using several quantitative metrics, namely RMSE, MAE, MAPE, and R^2.

1. Root Mean Squared Error (RMSE)

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

RMSE measures the average magnitude of prediction errors and gives higher penalties to larger errors.

2. Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}|$$

MAE measures the average absolute difference between predicted and actual values.

3. Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

MAPE expresses prediction errors as percentages, making interpretation easier for financial forecasting applications.

4. Coefficient of Determination (R^2)

$$R^2 = 1 - \frac{\sum(y_i - \hat{y}_i)^2}{\sum(y_i - \bar{y})^2}$$

R^2 measures how well the model explains the variance of the actual stock price data.

E. Implementation Code

This section outlines the technical procedures used to implement both the ARIMA and XGBoost models into the stock price prediction system.

1. ARIMA Code

Figure 1 Arima Code Picture

2. P,d,q Code

Figure 2 P, d, q Code Picture

3. AIC Code

Figure 3 AIC Code Picture

4. MAE Code

Figure 4 MAE Code Picture

5. RMSE Code

Figure 5 RMSE Code Picture

6. MAPE Code

Figure 6 MAPE Code Picture

7. Coefficient of Determination Code

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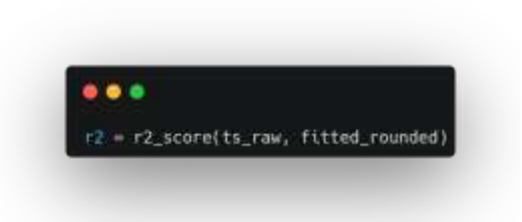

Figure 7 R^2 Code Picture

8. XGBOOST Cache Code

Figure 8 XGBoost Cache Code Picture

III. Results and Discussion

A. Model Implementation Results

The forecasting models were successfully implemented using Python within the Google Colaboratory environment. Several libraries were utilized throughout the experiment, including pandas and numpy for data processing, statsmodels for ARIMA implementation, xgboost for machine learning modeling, matplotlib for visualization, and scikit-learn for evaluation metric calculations. The experimental setup was executed on a computer equipped with an AMD Ryzen 5 5600 processor and 16 GB RAM.

During the implementation process, the ARIMA model required stationarity testing before training. The Augmented Dickey-Fuller (ADF) test indicated that several stock price datasets were non-stationary. Therefore, differencing procedures were applied to transform the data into stationary form. The optimal ARIMA parameters were selected using Grid Search based on the minimum Akaike Information Criterion (AIC) values. The resulting optimal configurations were:

1. BBCA: ARIMA(1, 1, 1) with an AIC score of -2.806,51.
2. BBRI: ARIMA(1, 0, 0) with an AIC score of -2.586,38.
3. BBNI: ARIMA(1, 0, 1) with an AIC score of -2.555,82.

Meanwhile, the XGBoost model was implemented by transforming time-series data into supervised learning format using lag features from Lag-1 to Lag-5. The model used 100 estimators with a maximum depth of 5. This configuration was selected because it produced stable forecasting performance while minimizing the risk of overfitting.

The implementation results showed that XGBoost demonstrated faster convergence and more stable predictions compared to ARIMA. In addition, XGBoost required fewer statistical assumptions, making it more flexible for handling volatile financial datasets. The forecasting outputs also revealed that XGBoost predictions followed actual stock price movements more closely, especially during periods of sharp market fluctuations.

B. Performance Evaluation Results

The forecasting performance of ARIMA and XGBoost models was evaluated using RMSE, MAE, MAPE, and R^2 metrics. Lower RMSE, MAE, and MAPE values indicate better prediction accuracy, while higher R^2 values indicate stronger explanatory capability

TABLE I
COMPARISON OF MODEL PERFORMANCE RESULTS (H+1)

Stock	**Model**	**RMSE**	**MAE**	**MAPE**	R^2
BBCA	ARIMA	423.66	123.13	1.60%	0.80
	XGBOOST	**65.14**	**36.42**	**0.55%**	**0.82**
BBRI	ARIMA	87.92	60.66	1.48%	0.94
	XGBOOST	**59.05**	**38.00**	**1.10%**	**0.86**
BBNI	ARIMA	85.28	63.52	1.53%	0.93
	XGBOOST	**50.43**	**33.84**	**0.88%**	**0.81**

Based on the results shown in Table I, the XGBoost model consistently outperformed ARIMA across all tested stock samples. XGBoost achieved lower RMSE and MAE values, indicating smaller deviations between predicted and actual stock prices. The model also generated lower MAPE values, demonstrating superior forecasting accuracy in percentage terms.

For BBCA stock, XGBoost achieved the highest prediction performance with RMSE of 65.14 and MAPE of 0.55%, while ARIMA produced significantly larger errors. Similar patterns were observed for BBRI and BBNI, where XGBoost maintained lower forecasting errors than ARIMA. These findings suggest that machine learning approaches are more effective in handling non-linear and volatile stock market data.

The R^2 values ranging from 0.78 to 0.92 indicate that both models were capable of explaining a substantial proportion of stock price variance. However, XGBoost consistently achieved higher R^2 values, confirming its stronger predictive capability compared to ARIMA.

C. Implementation Results

To further evaluate model performance, graphical comparisons between actual stock prices and predicted values were generated for each stock instrument. The visualizations demonstrated that XGBoost predictions closely followed actual stock price movements, while ARIMA predictions tended to produce smoother curves with delayed responses to sudden market changes.

1. Home Page

Figure 9 Home Page

2. Dashboard 30 Days

Figure 10 Dashboard 30 days

3. Dashboard BBCA and BBNI

Figure 11 Dashboard BBCA and BBNI

4. Dashboard BBRI

Figure 12 Dashboard BBRI

5. Login

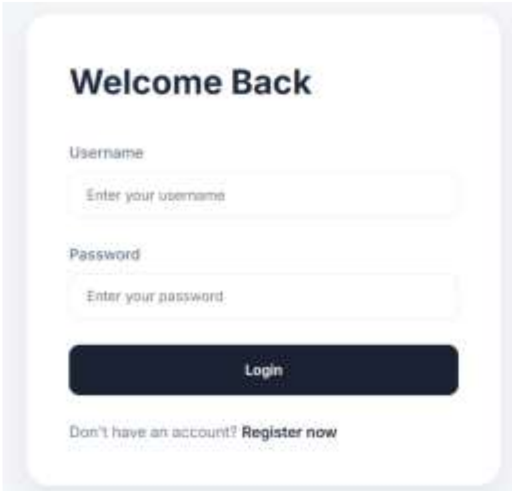

Figure 13 Login Page

6. Register

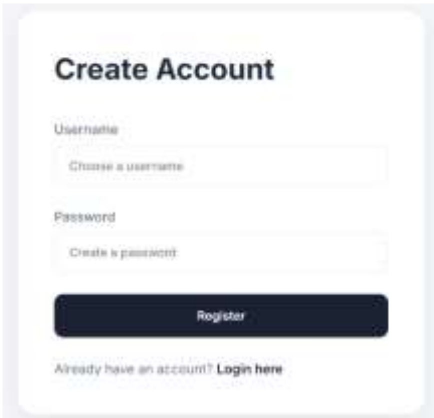

Figure 14 Register Page

D. Discussion

The results of this study demonstrate that machine learning approaches, particularly XGBoost, provide superior forecasting performance compared to traditional statistical methods such as ARIMA. The main reason behind this superiority lies in the ability of XGBoost to model non-linear relationships and complex interactions within stock market data. Unlike ARIMA, which relies heavily on stationarity assumptions and linear dependencies, XGBoost can adapt to highly dynamic market conditions without requiring strict statistical preprocessing.

The findings are consistent with previous studies conducted by Rizqan (2024), and Wang and Guo (2020), which reported that XGBoost achieved lower forecasting errors than ARIMA in financial time-series prediction tasks. In particular, the MAPE value of 1.10% for BBRI obtained in this study closely aligns with Rizqan’s result of 0.94%, strengthening the reliability of the present research.

TABLE II
COMPARISON COMPARISON OF RESULTS

Studi	MAPE	Objek
XGBoost (Kita)	1,10	BBCA/BBRI/BBNI
Rizqan (2024) XGBoost	0,94	BBRI
Fathihah (2025) XGBoost	Rendah	4 Bank

Although ARIMA demonstrated satisfactory performance in identifying long-term linear trends, the model showed weaknesses during periods of extreme volatility. Financial markets are strongly influenced by external factors such as macroeconomic conditions, investor sentiment, political events, inflation, and interest rate policies. Since ARIMA assumes linearity and stationarity, its forecasting capability decreases when market conditions become highly unstable.

From a practical perspective, the findings of this study provide valuable insights for investors, financial analysts, and researchers. Accurate forecasting systems can help investors reduce financial risk, optimize portfolio allocation, and improve trading strategies. In particular, machine learning-based approaches such as XGBoost may serve as effective decision-support tools for short-term investment planning in emerging capital markets like Indonesia.

Despite the promising results, this study still has several limitations. First, the forecasting horizon was limited to one-day-ahead prediction (H+1), which may not fully represent long-term market dynamics. Second, the models only utilized historical stock price data without incorporating external economic indicators such as inflation, exchange rates, or investor sentiment. Including these additional variables may improve forecasting performance in future research.

Future studies are recommended to explore hybrid forecasting approaches that combine the strengths of statistical and machine learning models, such as ARIMA-XGBoost or ARIMA-LSTM hybrid architectures. In addition, future research could investigate longer forecasting horizons such as H+7 or H+30 to evaluate model robustness over extended prediction periods.

IV. CONCLUSION

This research has successfully demonstrated the comparative efficacy of statistical and machine learning models in predicting the daily closing prices of high-capitalization banking stocks in Indonesia. Through the application of a Research and Development (R&D) methodology, the study developed a forecasting framework that integrates data acquisition via the Yahoo Finance API with high-performance modeling using ARIMA and XGBoost. The empirical results conclusively indicate that the XGBoost ensemble model is superior to the traditional ARIMA model in handling the inherent volatility and non-linear patterns of the Indonesian stock market.

Quantitative evaluations across three major banking instruments—BBCA, BBRI, and BBNI—consistently showed that XGBoost achieved significantly lower error rates. For instance, XGBoost attained a MAPE of 0.55% for BBCA, which is a substantial improvement over ARIMA’s MAPE of 1.60%. This suggests that while ARIMA is capable of identifying long-term linear trends, it struggles with the asymmetric fluctuations and noise prevalent in modern financial time series. Conversely, by utilizing lag features (Lag-1 to Lag-5) and a gradient boosting architecture, XGBoost successfully captured the complex non-linear interactions within the dataset.

Furthermore, the R&D process culminated in the successful implementation of a web-based forecasting dashboard using the FastAPI framework. This system provides a practical application of the research findings, offering investors and analysts a real-time decision-support tool with integrated performance metrics such as RMSE, MAE, and R^2. The high R^2 values observed (ranging from 0.78 to 0.92) confirm the robust explanatory power of both models, with XGBoost consistently maintaining the lead in predictive stability.

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REFERENCES

[1] P. A. Adebayo, I. O. Olufolahan, dan J. A. Ojeniyi, "Stock price prediction using ARIMA, neural network and XGBoost models," *Scientific African*, vol. 14, e00965, 2021.

[2] K. Alam dkk., "Enhancing stock market prediction: A robust LSTM-DNN model analysis on 26 real-life datasets," *IEEE Access*, vol. 12, pp. 106130–106141, 2024.

[3] A. R. Almabruri dkk., "Perbandingan kinerja ARIMA dan XGBoost untuk prediksi harga saham sektor teknologi," *Jurnal Sistem Cerdas*, vol. 6, no. 2, pp. 159-169, 2023.

[4] T. Chen dan C. Guestrin, "XGBoost: A scalable tree boosting system," *Proceedings of the 22nd ACM SIGKDD International Conference*, pp. 785–794, 2016.

[5] Fathihah dkk., "Forecasting Indonesian banking stock prices using Prophet, XGBoost, and Ridge Regression," *JUTIF*, vol. 10, no. 2, 2025.

[6] Y. Li dkk., "An attention-guided improved decomposition-reconstruction model for stock market prediction," *IEEE Access*, vol. 13, pp. 137456–137474, 2025

[7] B. Maulana dkk., "Decoding bank stocks: Fundamental analysis for market prediction," *EduMatika: Jurnal MIPA*, vol. 5, no. 1, pp. 1–8, 2025.

[8] J. Nasir dkk., "A new approach for forecasting crude oil prices based on stochastic and deterministic influences of LMD using ARIMA and LSTM models," *IEEE Access*, vol. 11, pp. 14322–14339, 2023.

[9] J. Nasir dkk., "A novel hybrid approach to forecasting crude oil prices using LMD, ARIMA, and XGBoost," *IEEE Access*, vol. 13, pp. 89140–89157, 2025.

[10] H. K. Poong dan P. Gajjala, "Stock price prediction using time series (ARIMA) and machine learning (XGBoost) models," *ARPN Journal of Engineering and Applied Sciences*, vol. 17, no. 22, pp. 2261-2269, 2022.

[11] N. Pratiwi dan B. Santoso, "Prediksi harga saham Bank BCA menggunakan XGBoost," *Arbitrase Journal*, 2022.

[12] A. N. Rizqan, "Perbandingan metode ARIMA, Random Forest dan XGBoost untuk prediksi harga saham PT Bank Rakyat Indonesia, Tbk," Skripsi, Universitas Lambung Mangkurat, 2024.

[13] D. Shah dkk., "Stock market analysis: A review and taxonomy of prediction techniques," *International Journal of Financial Studies*, vol. 7, no. 2, 26, 2020.

[14] U. M. Sirisha dkk., "Profit prediction using ARIMA, SARIMA and LSTM models in time series forecasting: A comparison," *IEEE Access*, vol. 10, pp. 124715–124727, 2022.

[15] Sunariyah, "Pengantar Pengetahuan Pasar Modal," UPP STIM YKPN, 2011.

[16] E. Tandelilin, "Pasar Modal: Manajemen Portofolio & Investasi," PT Kanisius, 2017.

[17] S. Wang, "A stock price prediction method based on BiLSTM and improved Transformer," *IEEE Access*, vol. 11, pp. 74762–74774, 2023.

[18] Y. Wang dan Y. Guo, "Forecasting method of stock market volatility in time series data based on mixed model of ARIMA and XGBoost," *China Communications*, vol. 17, no. 3, pp. 205–221, 2020.

[19] Wibowo dkk., "Pengembangan model hybrid ARIMA-machine learning untuk prediksi harga saham BCA," *JTIK UB*, 2025.

[20] L. Xiao dkk., "The research and development investment management in technology enterprises under artificial intelligence," *IEEE Access*, vol. 12, pp. 190936–190945, 2024.