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Forecasting Indonesian Banking Stock Prices Using Prophet, XGBoost, and Ridge Regression: A Comparative Analysis

Tony*[1], Manlika Ratchagit[2], Lely Hiryanto[3]

[1,3]Faculty of Information Technology, Universitas Tarumanagara, Indonesia
[2]Program in Statistics and Information Management, Faculty of Science, Maejo University, Thailand

Email: [1]tony@fti.untar.ac.id

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Abstract

This study investigates the efficacy of Prophet, XGBoost, and Ridge Regression in forecasting stock prices of four major Indonesian banks—Bank Central Asia (BBCA.JK), Bank Negara Indonesia (BBNI.JK), Bank Rakyat Indonesia (BBRI.JK), and Bank Mandiri (BMRI.JK)—using daily historical data from January 2020 to March 2025, sourced from Yahoo Finance. The banking sector's volatility, evidenced by year-to-date declines ranging from 7.59% (BBCA) to 22.69% (BMRI) as of May 1, 2025, underscores the need for accurate predictive models. Performance was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), revealing Ridge Regression as the superior method, consistently achieving the lowest errors (i.e., MAE of 23.81 for BBNI.JK and RMSE of 55.75 for BBCA.JK). Prophet exhibited the highest errors, suggesting its seasonal focus is less suited to stock price unpredictability, while XGBoost performed moderately better but lagged behind Ridge Regression. The results highlight Ridge Regression's effectiveness in handling multicollinearity and noise in financial data. Our discussions emphasize the importance of model selection based on data characteristics, with implications for investment decision-making in the Indonesian market. This research contributes to the field of computational finance by providing a comparative analysis that not only identifies Ridge Regression as a superior method for forecasting stock prices but also illuminates the limitations of popular models like Prophet and XGBoost in handling financial data's unique characteristics, guiding future model selection and development. Future research could explore hybrid models to enhance accuracy across varied market conditions, addressing the study's 60-day forecasting horizon limitation.

Keywords: *Indonesian banks, performance metrics, ridge regression, stock price forecasting.*

1. INTRODUCTION

Stock forecasting is essential in the investment domain, offering insights that empower traders and financial analysts to make informed decisions regarding future price fluctuations. An accurate stock price prediction method assists investors in generating profit through the strategic buying or selling of stocks at designated prices [1]. Numerous modelling approaches, such as Long Short-Term Memory (LSTM) networks [2][3], Autoregressive Integrated Moving Average (ARIMA) models [4][5], Facebook's Prophet [6][7], and Ridge Regression [8], have surfaced with the development of sophisticated analytical techniques. With the ability to handle the intricacies of financial data and identify underlying patterns across a 60-day forecasting horizon, each of these approaches offers distinct advantages. Since the stock market is inherently unpredictable, these methods aid in identifying trends that may result in more precise and trustworthy price forecasts.

The banking industry in Indonesia is thriving and vital to the national economy. Four banks, i.e., Bank Central Asia (BCA) [9], Bank Rakyat Indonesia (BRI) [10], Bank Mandiri [11], and Bank Negara Indonesia (BNI) [12], stand out among the other financial institutions because of their stability, expansion potential, and market performance. In addition to controlling the local banking system, these

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banks also draw a lot of interest from stock market investors. A number of variables, including as the state of the economy, modifications to regulations, and general market mood, affect their stock values. Investors and other stakeholders interested in the Indonesian financial market might gain important insights from an understanding of these institutions' performance. We will examine each bank's salient features in this investigation, such as market capitalization, stock price patterns, and the fundamental elements influencing their performance.

The top four Indonesian banks' stock values as of May 1, 2025, have performed differently, which reflects the market's volatility. Despite a 7.59% decline in year-to-date performance, Bank Central Asia (BBCA) remains the market leader with a substantial market capitalization, trading at IDR 8,825. Although it is still in a strong position, Bank Rakyat Indonesia (BBRI) has seen a more significant year-to-date decline of 19.12%, trading at IDR 3,850. With a stock price of IDR 4,890 and a year-to-date decline of 22.69%, Bank Mandiri (BMRI) has seen the biggest decline of the top four. Bank Negara Indonesia (BBNI), on the other hand, has performed marginally better, declining 13.46% so far this year. Its stock is currently trading at IDR 4,180. These numbers show that although the banking industry is still vital to the Indonesian economy, a few variables have affected the performance of these top banks' individual stocks this year.

In the dynamic realm of financial markets, the precise forecasting of stock prices remains a formidable challenge and a pursuit of paramount importance for investors, analysts, and financial institutions alike. The ability to accurately predict future stock prices can unlock lucrative investment opportunities, inform risk management strategies, and contribute to the overall stability of financial systems [13]. Consequently, a diverse array of forecasting methodologies has emerged, each leveraging unique theoretical underpinnings and computational techniques to decipher the intricate patterns embedded within stock market data. These methodologies span from traditional time series analysis, such as Autoregressive Integrated Moving Average, to more sophisticated machine learning approaches like Long Short-Term Memory networks, Prophet, XGBoost, and regression models, each possessing distinct strengths and limitations in capturing the complexities of stock price dynamics [14]. The selection of the most appropriate forecasting model hinges on a multitude of factors, including the characteristics of the specific stock under consideration, the availability of historical data, the desired level of accuracy, and the computational resources at hand [15]. As financial markets evolve and become increasingly interconnected, the quest for more accurate and robust stock price forecasting models remains an ongoing endeavour, demanding continuous exploration and refinement of existing methodologies [13].

The following studies collectively explore advanced statistical, machine learning, and deep learning approaches for predicting stock prices and analyzing market dynamics in the banking sectors of emerging markets. Mallick *et al*. [16] developed a novel glide path model using Principal Component Analysis (PCA) and multivariate regression to predict stock prices of five major Indian banks listed in the NIFTY50 index, with the first Principal Component (PC1) as the dependent variable and NIFTY50 and INR-USD as independent variables. The model demonstrated robustness and accuracy, validated through various performance indicators and Monte-Carlo simulations, effectively capturing historical stock price dynamics even during periods of fiscal stress.

Chen *et al*. [17] introduced a hybrid deep learning approach that enhances stock price prediction for Chinese commercial banks by integrating an improved K-means clustering algorithm using Dynamic Time Warping (DTW) with a Long Short-Term Memory (LSTM) neural network to cluster and predict stock price trends. The model, which employes multi-step output for static long-term forecasts, outperforms traditional single models in accuracy and generalization, as evidenced by metrics like R^2, MAE, and MSE, aiding investors and companies in making profitable decisions.

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Arif *et al*. [18] developed a stock price prediction model for PT Bank Jago Tbk. using machine learning algorithms, integrating historical stock price data with market sentiment extracted from X posts via Natural Language Processing (NLP)-based sentiment analysis. The linear regression model yielded the highest accuracy with lower MAE and RMSE, revealing that sentiment analysis from X has limited impact on predictions for this bank, though its broader influence on other companies or sectors merits further investigation.

Zein *et al*. [19] compared the Neural Basis Expansion Analysis for Interpretable Time Series (N-BEATS) with Long Short-Term Memory (LSTM) architectures to predict stock prices of PT Bank Central Asia Tbk using historical data from March 2013 to March 2023, aiming to enhance investment decision-making. The N-BEATS model, noted for its interpretability and faster training, outperforms LSTM with a lower Mean Average Percentage Error (MAPE) of 1.05%, demonstrating its effectiveness in forecasting stock prices and aiding investors in maximizing profits.

Ulyah *et al*. [20] investigated the impact of COVID-19 on Indonesia's financial system, focusing on the Jakarta Composite Index (JCI) and state-owned bank stocks, using Multivariate Regression with Time Series Errors to analyze price fluctuations and dependencies. The findings confirmed a significant pandemic effect on the JCI and bank stock prices, with a notable dependency between them, influenced by a variable representing three phases of the pandemic based on new confirmed cases.

Widjaja and Ariefianto [21] studied the relationship between bank stock prices and key fundamentals—profitability, credit risk, and liquidity risk—using the dynamic common correlated effect (DCCE) technique, revealing an error-correction mechanism that equilibrates stock prices within 2.62 to 3.22 months. The findings confirm that profitability, measured by ROE (Return on Equity) and NIM (Net Interest Margin), positively influences stock prices, while credit and liquidity risk measures show no significant impact.

Sulistianingsih and Martono [22] conducted a comparative analysis of deep learning and hybrid models, including LSTM, CNN, CNN-LSTM, and LSTM-CNN, for predicting stock movements in the Indonesian banking sector, finding that the LSTM-CNN hybrid consistently outperforms others in terms of RMSE and MAE. The research highlighted the importance of hyperparameter tuning in optimizing model performance, providing valuable insights for financial market stakeholders and suggesting further exploration in model optimization to enhance prediction accuracy.

Satria [23] aimed to identify the most suitable model for predicting stock prices of four major Indonesian banks (BRI, BNI, BCA, and Mandiri) from 2013 to 2022, comparing statistical learning with ARIMA Box-Jenkins and deep learning methods like RNN, LSTM, and GRU. The findings indicated that GRU provided the best performance for stock price prediction, while ARIMA Box-Jenkins was found to be unsuitable.

Haryono *et al*. [24] compared the performance of various deep learning architectures, including combinations of CNN, GRU, LSTM, and GCN layers, to forecast stock prices for 727 companies listed on the Indonesia Stock Exchange (IDX). Using a dataset of over 2.5 million rows, the TFGRU architecture was identified as the best performer, yielding the finest results for 315 companies.

Syukur and Istiawan [25] compared the performance of 10 different machine learning classification algorithms to predict the stock price direction of the LQ45 index on the Indonesia Stock Exchange. The results showed that the Random Forest algorithm had the best performance, while other models like Classification and Regression Trees, C4.5, Support Vector Machine, and Logistic Regression also performed well.

Simarmata *et al*. [26] analyzed the performance of portfolio optimization by forecasting Indonesian bank stocks (BBCA.JK, BBNI.JK, BBRI.JK, BBTN.JK, BMRI.JK) from 2020 to 2023 using R software, with forecasting methods including SES, DES, SMA, DMA, and ARIMA, selecting the best method based on the smallest SSE, MSE, RMSE, and MAPE values. The SES method was identified as

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the best for forecasting stocks of Bank BCA, BNI, BRI, and BTN, while the ARIMA method was most accurate for Bank Mandiri's stock data.

Fathihah *et al*. [27] introduced an XGBoost-based machine learning model to predict stock returns for five Indonesian banking institutions using data from January 2021 to November 2023, incorporating technical indicators and hyperparameter tuning via grid search. The model achieved high accuracy with an error rate below one percent, demonstrating its effectiveness as a robust tool for enhancing investment prediction strategies in the financial sector.

While these studies showcase diverse ML (Machine Learning) and DL (Deep Learning) approaches, there is a notable gap in comparative analyses specifically involving Prophet, XGBoost, and Ridge Regression for Indonesian banking stocks. Prophet's strength in handling seasonality, XGBoost's ability to integrate complex features, and Ridge Regression's computational efficiency remain underexplored in this context. The unique dynamics of Indonesia's banking sector, influenced by local economic policies and global factors, warrant a focused comparison to identify the most effective model for accurate forecasting and investment decision-making.

The problem is the inherent difficulty in accurately forecasting stock prices due to the complex, volatile, and unpredictable nature of financial markets. Despite the development of various modelling approaches such as LSTM, ARIMA, Prophet, and Ridge Regression, predicting stock prices remains a challenging task. This difficulty is compounded in the context of the Indonesian banking sector, where stock performances of major banks show significant volatility influenced by economic and regulatory factors. The challenge lies in selecting and applying the most suitable forecasting methods to generate reliable predictions that can support investment decisions and risk management, especially given the dynamic and interconnected nature of financial data.

The goals of this study are to:

- Analyze the performance of major Indonesian banks' stock prices and understand the factors influencing their fluctuations.
- Compare the effectiveness of different forecasting models, such as LSTM, ARIMA, Prophet, and Ridge Regression, in predicting stock prices over a 60-day horizon.
- Identify the most suitable modelling approach for accurate and reliable stock price prediction in the context of the Indonesian financial market.
- Contribute to the ongoing development of robust forecasting methodologies that can adapt to the evolving and interconnected nature of financial markets, ultimately aiding investors and stakeholders in making informed decisions.

2. METHOD

In this work, we use three techniques, including Prophet, XGBoost, and Ridge regression. **Figure 1** shows a machine learning-based research methodology for stock price prediction. The process begins with stock price data, which undergoes a data pre-processing step to prepare it for analysis. We implement critical preprocessing procedures, encompassing normalization and data reshaping, to adequately prepare the dataset for subsequent modeling. After this, the cleaned data is divided into a training set and a testing set. We divide the dataset into 70% training and 30% testing to evaluate model performance effectively. The training set is used to train three distinct forecasting models: Prophet, XGBoost, and Ridge Regression. The performance of these trained models is then assessed in the model evaluation phase using the testing set, ultimately concluding the process.

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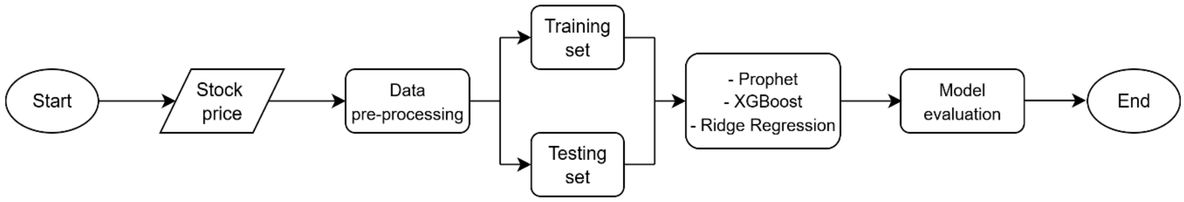

Figure 1. Research methodology.

2.1. Data

In this stock price forecasting study, the dataset was obtained from Yahoo Finance website (https://finance.yahoo.com/), which provides public and real-time historical stock price data. The dataset used includes daily stock data from four different entities in the Indonesia banking sector listed on the Indonesia Stock Exchange (IDX), i.e., (i) Bank Central Asia (BBCA.JK), (ii) Bank Rakyat Indonesia (BBRI.JK), (iii) Bank Mandiri (BMRI.JK), and (iv) Bank Negara Indonesia (BBNI.JK). We extract the data between January 2020 and March 2025 for a total of 1,269 prices. This information is called OHLCV. **Table 1** shows the sample dataset used in this work.

Table 1. Sample Dataset.

Date	Ticker	Open	High	Low	Close	Adj Close	Volume
25/03/2025	BBRI.JK	3660.0	3840.0	3660.0	3800.0	3800.0	331285900
25/03/2025	BMRI.JK	4500.0	4810.0	4500.0	4740.0	4740.0	313034100
26/03/2025	BBCA.JK	8300.0	8650.0	8275.0	8525.0	8525.0	283104600
26/03/2025	BBNI.JK	4010.0	4280.0	4000.0	4250.0	4250.0	229422000
26/03/2025	BBRI.JK	3870.0	4020.0	3860.0	4000.0	4000.0	540888800
26/03/2025	BMRI.JK	4980.0	5175.0	4930.0	5150.0	5150.0	582172700
27/03/2025	BBCA.JK	8425.0	8575.0	8375.0	8500.0	8500.0	122943900
27/03/2025	BBNI.JK	4250.0	4280.0	4110.0	4240.0	4240.0	101189600
27/03/2025	BBRI.JK	4000.0	4050.0	3930.0	4050.0	4050.0	322553200
27/03/2025	BMRI.JK	5150.0	5250.0	5050.0	5200.0	5200.0	301025300

Figure 2 and **Figure 3** show "Adjusted Closing Price" of four different Indonesian bank's stock over time, i.e., BBCA.JK, BBNI.JK, BBRI.JK, and BMRI.JK, from early 2020 to March 2025. The prices are plotted in Indonesian Rupiah (IDR). All four banks show a general upward trend in their stock prices from 2020 until early 2025, followed by a noticeable decline in the first half of 2025. This suggests a common market influence affecting the Indonesian banking sector. The initial dip in early 2020 for all banks likely corresponds to the economic shock from the COVID-19 pandemic.

Figure 2(a): Adjusted Closing Price of BCA. It starts around IDR 4,000-6,000 in 2020 and peaks above IDR 10,000 in early 2025 before declining to around IDR 8,000-9,000. The performance shows strong, relatively consistent growth over the period, making it the highest-priced stock among the four by 2025. This aligns with BCA's reputation as a blue-chip stock in Indonesia. The decline in 2025 is visible but less steep in percentage terms compared to some others.

Figure 2(b): Adjusted Closing Price of BNI. It starts around IDR 1,500-3,500 in 2020 and reaches a peak above IDR 5,500 in early 2025, then falls back towards IDR 4,000. BNI exhibits significant volatility, especially the sharp dip in early 2020 and a more pronounced drop in 2025 compared to BCA. It generally shows a strong recovery and growth path from 2020-2024.

Figure 3(a): Adjusted Closing Price of BRI. It starts around IDR 1,500-3,500 in 2020 and reaches a peak close to IDR 6,000 in early 2024, followed by another peak in late 2024 before a significant

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decline in 2025 to around IDR 3,000-4,000. BRI shows strong growth from 2020 to 2024. It appears to have a more noticeable decline in 2025 than BCA, bringing its price closer to its 2021-2022 levels. BRI is known for its focus on micro, small, and medium enterprises (MSMEs).

Figure 3(b): Adjusted Closing Price of Bank Mandiri. It starts around IDR 2,000-3,000 in 2020 and peaks above IDR 7,000 in early 2025, then declines to around IDR 4,000-5,000. Bank Mandiri demonstrates a generally strong and steady upward trend from 2020 to early 2025, similar to BCA in consistency but at a lower price point. The decline in 2025 is evident, but the stock remains significantly higher than its 2020-2021 levels.

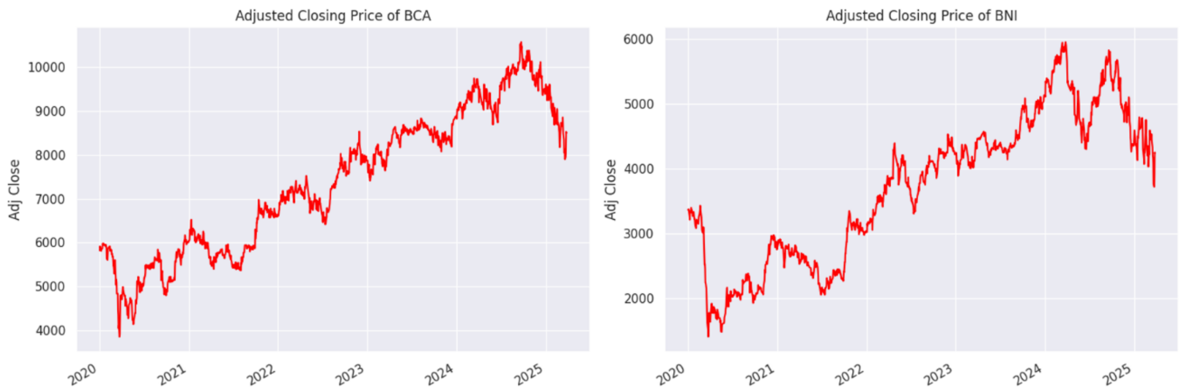

Figure 2. Adjusted Closing Price of **(a)** BBCA.JK and **(b)** BBNI.JK

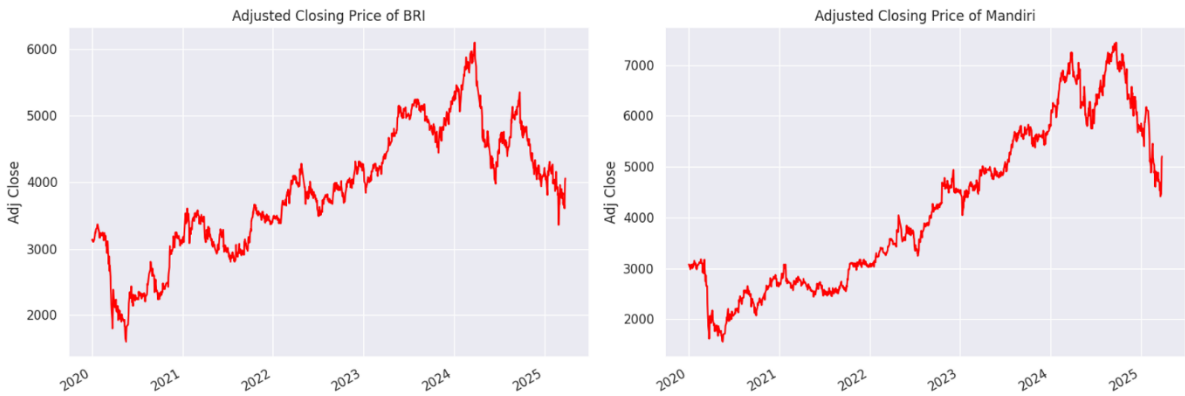

Figure 3. Adjusted Closing Price of **(a)** BBRI.JK and **(b)** BMRI.JK

The Adjusted Closing Price represents the closing price of a stock, modified to account for corporate actions such as dividends, stock splits, and new stock offerings. In contrast to the standard closing price, this adjusted figure incorporates these events to provide a more precise depiction of a stock's performance across time. This adjustment enables investors to evaluate the authentic value and growth trajectory of a stock, considering factors that influence its price yet do not necessarily reflect the company's underlying market performance.

2.2. Prophet

Prophet is a powerful and user-friendly tool for forecasting time series data. It's designed to be accessible to a wide range of users, including those without extensive statistical expertise, and it's particularly well-suited for business forecasting applications. Prophet is an open-source library from Meta's Core Data Science team for forecasting procedure implemented in R and Python. It is built to

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produce robust and accurate forecasts, especially for time series with strong seasonal effects and several seasons of historical data.

Prophet operates on an additive regression model, breaking down a time series into three main components, plus an error term, in Eq. 1:

$$\boldsymbol{y(t) = g(t) + s(t) + h(t) + \epsilon t} \qquad (1)$$

where:

- $\boldsymbol{y(t)}$ is the time series data at time t.
- $\boldsymbol{g(t)}$ is the trend component: This captures the non-periodic changes in the time series, representing the long-term increase or decrease in the data. Prophet can model this as a piecewise linear or logistic growth curve, automatically detecting "changepoints" where the trend significantly shifts.
- $\boldsymbol{s(t)}$ is the seasonality component: This accounts for recurring patterns at regular intervals, such as daily, weekly, or yearly cycles. Prophet uses Fourier series to model these seasonalities flexibly.
- $\boldsymbol{h(t)}$ is the holiday component: This allows for the inclusion of important holidays or special events that occur at irregular intervals but are known in advance (e.g., national holidays). Users can provide a custom list of these events.
- $\boldsymbol{\epsilon t}$ is the error term: This represents any unmodeled or random fluctuations in the data.

2.3. XGBoost

XGBoost (Extreme Gradient Boosting) is an Ensemble Learning algorithm that relies on a decision tree structure and applies a Gradient Boosting approach in the process. Different from Linear Regression which assumes a linear relationship, XGBoost is able to model complex non-linear relationships between features with high accuracy. In this research, XGBoost is used as a comparison model against Linear Regression to predict airline stock prices, with the hope that the complexity of the XGBoost algorithm can capture hidden patterns that are not identified by linear models.

The basic principle of XGBoost is an iterative modeling technique, where each subsequent tree is built with the aim of improving the prediction error of the previous tree model. The final model is an accumulation of the predictions of all the trees built. In general, the XGBoost prediction at the t-th iteration can be expressed as:

$$\boldsymbol{\hat{y}\mathrm{i}^{(t)} = \sum k = 1^{(t)} f_k(x_i)\,,\ f_k \in F} \qquad (2)$$

In this model (see Eq. 2), the predicted value at iteration t is denoted as $\boldsymbol{\hat{y}\mathrm{i}^{(t)}}$, which is the accumulation of all decision tree function outputs up to that iteration. Each $\boldsymbol{f_k}$ represents the decision tree function at iteration k, while F is the set (space) of all decision trees that can be formed by the model. The objective function minimized by XGBoost consists of two main components, namely the loss function and the regularization function. The loss function is used to measure the magnitude of the prediction error between the actual value and the predicted value, while the regularization function serves to control the complexity of the model to prevent overfitting. Mathematically, the objective function is written as follows:

$$\boldsymbol{L(\phi) = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{t} \Omega\,(f_k)} \qquad (3)$$

In Eq. 3, L is the loss function used to calculate the difference between the predicted value and the actual value, with one example being mean squared error (MSE). Meanwhile, $\boldsymbol{\Omega\,(f_k)}$ is a regularization function that measures and controls the complexity of decision tree k, thereby helping to prevent overfitting by penalizing overly complex models. By minimizing the function $\boldsymbol{L(\phi)}$, XGBoost

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strives to achieve an optimal balance between prediction accuracy and model complexity, thereby improving generalization to previously unseen data.

2.4. Regression Model

Ridge regression is a widely used technique in statistical modelling and machine learning, particularly in the context of linear regression. It's a type of regularization method that aims to address some common problems encountered when fitting linear models, such as multicollinearity and overfitting.

In linear regression, we try to model the relationship between a dependent variable (denoted as *Y*) and one or more independent variables (features, denoted as $X_1, X_2 \cdots X_p$) using a linear equation in Eq. 4:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_p X_p + \epsilon \qquad (4)$$

where:

- Y is the dependent variable.
- $X_1, X_2, \cdots X_p$ are the independent variables.
- β_0 is the intercept.
- $\beta_1, \beta_2, \cdots \beta_p$ are the coefficients (or weights) that represent the change in Y for a one-unit change in the corresponding X, holding other variables constant.
- ϵ is the error term.

The goal of linear regression is to find the values of these coefficients (β) that minimize the sum of squared errors (SSE), also known as the Residual Sum of Squares (RSS) (see Eq. 5), between the observed y values and the predicted $\hat{y}$ values.

$$RSS = \sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \qquad (5)$$

2.5. Model Evaluation

We use two performance metrics in this works:

a. Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is an evaluation metric used to measure the average absolute error between actual values and predicted values generated by a model. In this study, MAE is used to evaluate how far the stock price predictions generated by the model differ from the actual values in the same units. Mathematically, the MAE formula can be written as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \qquad (6)$$

The formula in Eq. 6 describes the average of the absolute difference between the actual value (y_i) and the predicted value ($\hat{y}_i$) of all data consisting of n observations, thus providing a measure of how large the model's prediction error is in units that are the same as the original data without taking into account the direction of the error. The smaller the MAE value obtained, the better the model's performance in making predictions, as it indicates a low average deviation from the actual data.

b. Root Mean Squared Error (RMSE)

Root Mean Squared Error (RMSE) is a metric used to measure the root of the mean square error between actual values and predicted values. RMSE places greater emphasis on large prediction errors than MAE, due to the squaring involved in its calculation. In the context of this study,

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RMSE is used to determine the extent of deviation between stock price predictions and actual values in a form that is more sensitive to outliers. The formula for calculating RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \quad (7)$$

where y_i is the actual value, $\hat{y}_i$ is the predicted value at time *t*, and *n* is the size of observation. This formula (Eq. 7) describes the size of the prediction error obtained by calculating the average of the squared difference between the actual value (y_i) and the predicted value ($\hat{y}_i$) for all data consisting of n observations, then taking the square root so that the result is in the same unit as the original data, so that the smaller the RMSE value, the better the accuracy of the model in predicting. A low RMSE value indicates that the model has better predictive performance.

3. RESULT

In this section, we describe the results of our works and the tests that have been carried out. We use Python programming on the Google Colaboratory (Google Colab) platform to do the experiments. **Table 2** presents a comparison of the performance of three different forecasting methods (Prophet, XGBoost, and Ridge Regression) for predicting the stock prices of four Indonesian banks (BBCA.JK, BBNI.JK, BBRI.JK, and BMRI.JK). The performance is evaluated using two common metrics, i.e., (i) MAE and (ii) RMSE.

It is immediately clear that Ridge Regression consistently outperforms both Prophet and XGBoost by a significant margin across all four stocks, achieving much lower MAE and RMSE values. This suggests that for this specific dataset and forecasting task, a simpler linear regression model with regularization (Ridge) is more effective than the more complex Prophet (additive time series model) and XGBoost (ensemble tree-based model).

We describe detailed breakdown per stock as follows:

1. BBCA.JK (Bank Central Asia):
   a. Prophet: High errors (MAE: 1389.91, RMSE: 1501.21).
   b. XGBoost: Significantly better than Prophet, but still high (MAE: 295.21, RMSE: 371.05).
   c. Ridge Regression: Exceptionally low errors (MAE: 42.44, RMSE: 55.75), indicating a very accurate forecast.
2. BBNI.JK (Bank Negara Indonesia):
   a. Prophet: High errors (MAE: 1234.97, RMSE: 1259.91).
   b. XGBoost: Better than Prophet, but still substantial (MAE: 154.51, RMSE: 214.95).
   c. Ridge Regression: Very low errors (MAE: 23.81, RMSE: 30.04), making it the best performer.
3. BBRI.JK (Bank Rakyat Indonesia):
   a. Prophet: High errors (MAE: 1444.63, RMSE: 1461.70).
   b. XGBoost: Better than Prophet, but still considerable (MAE: 104.20, RMSE: 160.90).
   c. Ridge Regression: Excellent performance with very low errors (MAE: 25.48, RMSE: 33.87).
4. BMRI.JK (Bank Mandiri):
   a. Prophet: High errors (MAE: 1610.14, RMSE: 1706.67).
   b. XGBoost: Better than Prophet, but substantial (MAE: 314.14, RMSE: 368.59).
   c. Ridge Regression: Achieves very low errors (MAE: 26.71, RMSE: 35.20)

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4. DISCUSSIONS

Ridge Regression Dominance: For this particular stock price forecasting task, Ridge Regression consistently provides the most accurate predictions as measured by MAE and RMSE. Its ability to handle multicollinearity and prevent overfitting seems to be highly beneficial here.

XGBoost vs. Prophet: XGBoost generally performs significantly better than Prophet for these stock prices. Prophet, which is designed for time series with strong seasonal components, might not be as well-suited for the characteristics of stock price data (which can be more noisy and less predictable in simple additive seasonal terms).

Error Magnitude: The errors for Prophet are often in the thousands, while for XGBoost they are in the hundreds. Ridge Regression brings the errors down to tens, indicating a much higher degree of accuracy in predicting the stock prices.

Ridge Regression consistently shows the lowest MAE and RMSE across all stocks, suggesting it is the most accurate method in this comparison. Prophet tends to have the highest errors, indicating it may be less suitable for these stocks, while XGBoost's performance varies but is generally better than Prophet.

Table 2. Evaluation metrics of the methods on four stocks.

STOCK	METHOD	MAE	RMSE
BBCA.JK	Prophet	1389.91	1501.21
	XGBoost	295.21	371.05
	Ridge Regression	42.44	55.75
BBNI.JK	Prophet	1234.97	1259.91
	XGBoost	154.51	214.95
	Ridge Regression	23.81	30.04
BBRI.JK	Prophet	1444.63	1461.70
	XGBoost	104.20	160.90
	Ridge Regression	25.48	33.87
BMRI.JK	Prophet	1610.14	1706.67
	XGBoost	314.14	368.59
	Ridge Regression	26.71	35.20

5. CONCLUSION

This study evaluated the performance of Prophet, XGBoost, and Ridge Regression in forecasting the stock prices of four major Indonesian banks—Bank Central Asia (BBCA.JK), Bank Negara Indonesia (BBNI.JK), Bank Rakyat Indonesia (BBRI.JK), and Bank Mandiri (BMRI.JK)—using historical data from January 2020 to March 2025. The results demonstrate that Ridge Regression consistently outperforms the other two methods across all stocks, achieving the lowest Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) values. This suggests that Ridge Regression's regularization effectively handles the multicollinearity and noise inherent in stock price data, making it a robust choice for this forecasting task.

In contrast, Prophet, designed for time series with strong seasonal patterns, exhibited the highest errors, indicating its limited suitability for the unpredictable nature of stock prices. XGBoost, while performing better than Prophet, still lagged behind Ridge Regression, suggesting that its complex ensemble approach may not fully capture the linear relationships present in the data. The superior performance of Ridge Regression highlights the importance of selecting a model that aligns with the data characteristics and forecasting horizon.

These findings underscore the potential of simpler, regularized linear models in financial forecasting, particularly for the Indonesian banking sector. However, the study's reliance on a 60-day forecasting horizon and specific dataset suggests the need for further research to validate these results across different timeframes and market conditions. Future work could explore hybrid models combining the strengths of Ridge Regression with advanced machine learning techniques to enhance prediction accuracy and adaptability in dynamic financial markets.

CONFLICT OF INTEREST

The authors declares that there is no conflict of interest between the authors or with research object in this paper.

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