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Article

The Use of Facebook Prophet in Predicting Stock Prices

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Abstract: This study examines the effectiveness of the Facebook Prophet model in predicting stock prices. The dataset consists of 1,214 daily stock-price observations obtained from Yahoo Finance for the period from July 30, 2019, to July 30, 2024. A quantitative time-series approach was applied by testing several Prophet configurations, including a basic model, the addition of external regressors, parameter adjustment, and combinations of these approaches. Model performance was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). The best performance was produced by the optimized model combining regressors and parameter tuning, with an MAE of 36.31 and an RMSE of 52.06. Overall, the model generated reasonably accurate short-, medium-, and long-term predictions, although forecast bias tended to increase as the prediction horizon became longer. These findings indicate that Facebook Prophet can serve as a supporting tool for analyzing stock-price trends based on historical data.

Keywords: Facebook Prophet; stock-price forecasting; time series; MAE; RMSE

1. Introduction

The stock market is one of the principal indicators of a modern economy because it reflects both a company's financial condition and investors' expectations of its future performance. Stock prices fluctuate in response to numerous factors, including macroeconomic conditions, government policies, inflation, exchange rates, and market sentiment [1]. Short-term changes in supply and demand also contribute substantially to stock-price dynamics [2]. This complexity makes stock-price forecasting a significant challenge in financial analysis and time-series modeling.

Previous studies have applied various methods to predict stock prices. Classical statistical models such as the Autoregressive Integrated Moving Average (ARIMA) have been widely used to forecast market indices and individual stock prices [3]. However, ARIMA has limitations in capturing nonlinear patterns and dynamic trend changes. To address these limitations, machine-learning and deep-learning approaches, including Long Short-Term Memory (LSTM), have gained attention because of their ability to capture long-term dependencies [4], [5]. Several studies have also compared forecasting algorithms in the context of the Indonesian capital market to identify models with the highest predictive accuracy [6].

As time-series forecasting methods have advanced, Facebook Prophet has emerged as an additive model designed to handle nonlinear trends, seasonal changes, and incomplete data more flexibly. Prophet can integrate trend components, annual and weekly seasonality, and holiday effects within a single framework. Previous studies have reported that Prophet provides competitive performance compared with ARIMA and

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several deep-learning models in various forecasting contexts, including commodity and stock prices [7], [8], [5].

Prophet has been applied to the prediction of various stocks and market indices. Riady [9] found that Prophet produced relatively stable predictions for BBCA and TLKM shares. In addition, external regressors have been shown to improve Prophet's predictive accuracy by incorporating variables associated with price movements [10], [11]. Other studies have confirmed that appropriate parameter configuration significantly affects model performance [12], [13].

Against this background, this study uses the shares of PT Bank Negara Indonesia (Persero) Tbk (BBNI) as its research object. BBNI is a state-owned bank with a large market capitalization and highly liquid shares on the Indonesia Stock Exchange. Its active and economically responsive price movements make BBNI an appropriate case for time-series analysis.

This study evaluates Facebook Prophet's ability to predict BBNI stock prices under several configuration scenarios. The scenarios include a basic model, the addition of regressors, parameter adjustment, and combinations of these approaches. Each configuration is tested to determine its effect on forecasting performance.

Forecast accuracy is evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), which quantify the differences between predicted and actual values [14], [15], [16].

2. Materials and Methods

This study applies a quantitative approach using time-series analysis to predict the stock price of PT Bank Negara Indonesia (Persero) Tbk (BBNI). Time-series analysis is appropriate because stock-price observations are chronological and exhibit temporal dependence, allowing trends and seasonal patterns to be examined systematically [3], [5].

The principal forecasting method is Facebook Prophet, an additive model that combines trend, seasonality, and holiday effects within a single mathematical framework [7], [8]. In general, the Prophet model is expressed as follows:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t$$

where $g(t)$ represents the trend component, $s(t)$ represents seasonality, $h(t)$ denotes holiday or special-event effects, and ε_t is the error term. This formulation is designed to handle nonlinear trends and structural changes flexibly [7].

The research procedure comprises data collection, data preprocessing, testing of several Facebook Prophet configurations, model evaluation, and selection of the best-performing model. These stages were organized systematically to support a structured and replicable research process. The complete research workflow is presented in Figure 1.

Figure 1. Research methodology workflow

2.1 Data Collection

The dataset consists of historical stock prices for PT Bank Negara Indonesia (Persero) Tbk (BBNI) obtained from Yahoo Finance. The data were downloaded in CSV format on July 31, 2024, and cover the period from July 30, 2019, to July 30, 2024. The final dataset contains 1,214 daily observations.

The dataset includes Date, Open, High, Low, Close, Adjusted Close, and Volume. Date indicates the trading date; Open, High, Low, and Close represent the corresponding daily prices; Adjusted Close accounts for corporate actions such as dividends and stock splits; and Volume indicates the number of shares traded during the period.

Yahoo Finance was selected because it provides accessible, consistent, and relatively complete historical stock data. The platform is also widely used in time-series research and financial analysis, making it suitable for the modeling requirements of this study.

2.2. Data Preprocessing

Preprocessing was conducted to ensure that the stock-price dataset was suitable for modeling with Facebook Prophet. Because the dataset contains daily historical observations, date consistency and data completeness were examined before model development.

1. Data Cleaning

The dataset was checked for missing price values and duplicate records in the Date column. These checks were necessary because inconsistent dates and missing observations can affect the formation of trends and seasonal patterns in a time-series model.

2. Data Transformation

After the dataset structure was verified, the input format was adjusted to meet Prophet's requirements. The Date column was converted to a datetime data type and renamed ds, while Adjusted Close was selected as the target variable and renamed y. Adjusted Close was used because it reflects corporate actions and is therefore more representative for analyzing price movements over time.

2.3 Model Configuration

Several Facebook Prophet configurations were tested to examine the effects of external regressors and parameter adjustment on stock-price forecasting performance. Five models were evaluated, each representing a different modeling strategy:

1. Model 1: Basic Prophet model
2. Model 2: Prophet with external regressors
3. Model 3: Prophet with parameter adjustment
4. Model 4: Prophet with regressors and parameter adjustment
5. Model 5: Optimized Prophet model with regressors and parameter tuning

2.4 Model Evaluation and Selection

Model performance was evaluated using Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). MAE measures the average absolute difference between predicted and actual values, whereas RMSE calculates the square root of the mean squared prediction errors and therefore imposes a greater penalty on large errors.

3. Results and Discussion

This section presents the results of stock-price forecasting using Facebook Prophet. It begins with the dataset and preprocessing results, followed by the tested model configurations, selection of the best model, performance evaluation, and analysis of forecasts across short-, medium-, and long-term horizons.

3.1 Data Collection

The study used 1,214 daily historical observations for BBNI obtained from Yahoo Finance for the period from July 30, 2019, to July 30, 2024.

The dataset contains Date, Open, High, Low, Close, Adjusted Close, and Volume. For model testing, the data were divided chronologically into a training period from July 30, 2019, to July 30, 2023, and a testing period from July 31, 2023, to July 30, 2024. This split enabled direct comparison between forecasts and actual prices during the test period.

3.2 Preprocessing Results

The preprocessing stage confirmed that the dataset contained no missing values and no duplicate entries in the Date column. Consequently, all 1,214 observations could be used without deletion or imputation.

The data structure was then adapted to Facebook Prophet's required format. Date was converted to datetime and renamed ds, while Adjusted Close was selected as the target variable and renamed y. Because Adjusted Close incorporates the effects of dividends and stock splits, it provides a more representative basis for stock-price time-series analysis.

Following these steps, the dataset was structured and ready for model training and evaluation.

3.3 Model Determination

The model configurations focused on two principal aspects: the addition of regressors and the adjustment of trend and seasonality parameters. Separating these aspects made it possible to observe their individual effects on forecast performance.

The first configuration served as the baseline and used Facebook Prophet's default settings without additional variables or parameter changes. Its results were used as a benchmark for assessing subsequent configurations.

The second model incorporated Open, High, Low, and Volume as regressors. These variables represent within-period price dynamics and trading activity and were expected to provide additional information for estimating the adjusted closing price.

The third and fourth models examined the effects of trend and seasonality parameter adjustment. Several parameter combinations were tested iteratively to observe how the model responded to medium-term data patterns. Each configuration produced a distinct error level.

The fifth model extended the previous experiments by tuning parameters according to the evaluation results obtained at each iteration. This process aimed to identify a configuration that provided high accuracy while maintaining forecast stability across several time horizons.

Accordingly, the evaluation considered not only error values but also the influence of regressors and parameter tuning on the consistency of model performance.

3.4 Model Evaluation and Best-Model Selection

Each model was evaluated using MAE and RMSE. Together, these metrics describe the average absolute forecast deviation and the effect of comparatively large errors. The results are presented in Table 1.

Table 1. Model evaluation results

Model	MAE	RMSE
Model 1: Basic Prophet	344.39	460.96
Model 2: Prophet with External Regressors	43.97	68.97
Model 3: Prophet with Parameter Adjustment	370.53	493.74
Model 4: Prophet with Regressors and Parameter Adjustment	42.55	55.99
Model 5: Optimized Prophet Model	36.31	52.06

As shown in Table 1, Models 1 and 3 produced substantially higher MAE and RMSE values than the other models. This result indicates that the default configuration and parameter adjustment without additional variables did not provide sufficient predictive accuracy.

Performance improved markedly in Models 2 and 4 after regressors were introduced. The reductions in MAE and RMSE demonstrate that the additional variables helped the model capture stock-price movements more effectively.

Model 5 achieved the lowest errors, with an MAE of 36.31 and an RMSE of 52.06. This result shows that optimized parameter tuning combined with regressors improved forecast accuracy consistently. Model 5 was therefore selected for further analysis.

3.5 Best-Model Testing Results

After model evaluation and selection, Model 5 was assessed across several forecasting horizons. The test period from July 31, 2023, to July 30, 2024, was used so that forecasts could be compared directly with actual prices for the same period.

1. Short-Term Forecast (One Week)

For the period from July 31 to August 7, 2023, the model generated a forecast of 4,320, while the actual price was 4,294. The difference of 26 points indicates a relatively small short-term deviation. Thus, during the initial test period, the model followed the price movement reasonably well. Figure 2 compares forecast and actual values for this period.

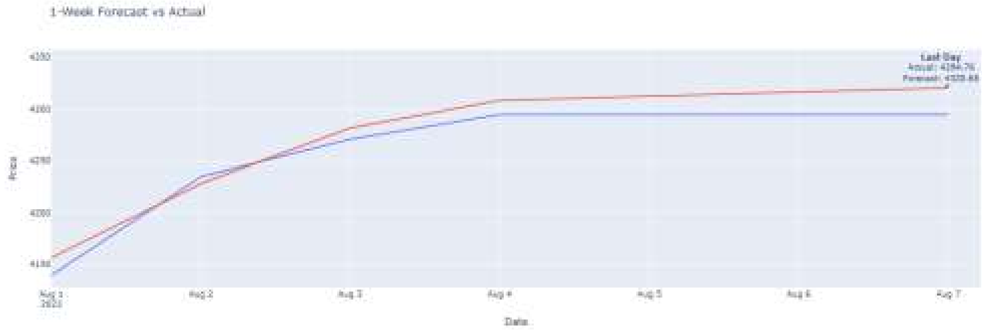

Figure 2. Forecast and actual stock prices over one week (July 31–August 7, 2023)

2. Medium-Term Forecast (One Month)

For the period from July 31 to August 31, 2023, the model produced a forecast of 4,408, compared with an actual value of 4,378. The difference remained relatively small, indicating that the model continued to track stock-price movements adequately. Figure 3 presents the one-month comparison.

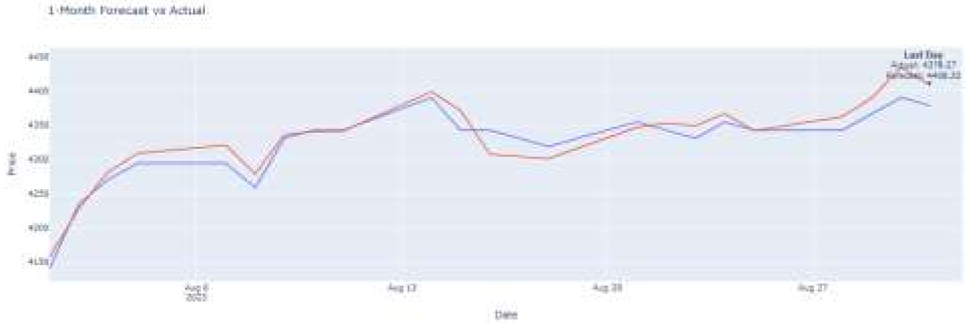

Figure 3. Forecast and actual stock prices over one month (July 31–August 31, 2023)

3. Medium-Term Forecast (Six Months)

For the six-month horizon ending January 31, 2024, the model produced a forecast of 5,519, while the actual price was 5,487. The deviation increased slightly compared with the shorter horizons but remained within a reasonable range. Figure 4 illustrates the forecast and actual price patterns over the six-month period.

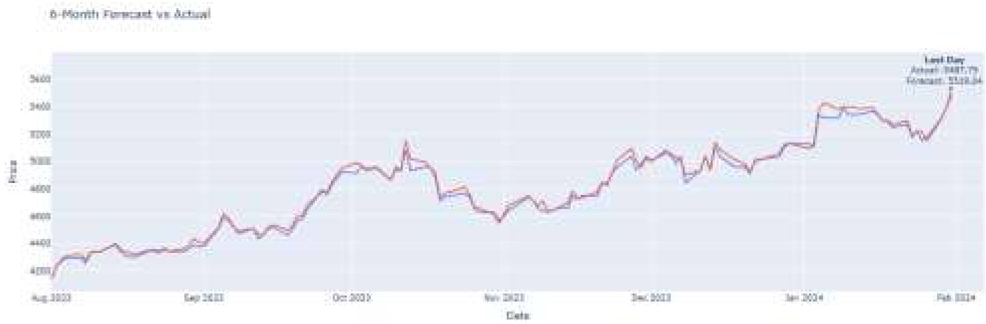

Figure 4. Forecast and actual stock prices over six months (July 31, 2023–January 31, 2024)

4. Long-Term Forecast (One Year)

For the one-year horizon ending July 30, 2024, the model generated a forecast of 4,944, while the actual price was 4,950. The largest discrepancy occurred on March 15, 2024, when the forecast of 5,588 differed from the actual value of 5,800. Nevertheless, the model generally followed the stock-price pattern throughout the test period. Figure 5 presents the long-term forecast results.

Figure 5. Forecast and actual stock prices over one year (July 31, 2023–July 30, 2024)

3.6 Bias Analysis for Long-Term Forecasting

The study proposed that forecast bias would increase as the prediction horizon became longer. The results show that bias tended to increase with the forecast period, although the increase was not substantial.

Although several long-term observations exhibited relatively large differences between forecast and actual values, Model 5 generally maintained acceptable predictive performance. This finding indicates that an optimally configured Facebook Prophet model can provide useful stock-price forecasts even over comparatively long horizons.

4. Conclusion

The findings demonstrate that Facebook Prophet, when combined with appropriate regressors and parameter tuning, can generate reasonably accurate stock-price forecasts from historical data.

For short-term forecasts, the model was stable and tracked actual price movements effectively. For medium- and long-term horizons ranging from six months to one year, forecast bias increased, but the resulting errors remained relatively small and acceptable. The addition of regressors and appropriate parameter settings therefore helped maintain prediction consistency across longer horizons.

The initial hypothesis that bias would increase significantly as the forecasting horizon expanded was not fully supported. Although relatively large differences occurred at specific points, including March 15, 2024, the model generally retained a strong ability to follow the direction and pattern of stock-price movements.

These findings suggest that Facebook Prophet is sufficiently reliable for modeling historical stock-price trends, particularly when supported by additional regressors and parameters tailored to the characteristics of the dataset. However, this study relies on historical backtesting, and the forecasts may not represent real-time market conditions. The results should therefore be treated as supporting information rather than as a sole basis for investment decisions, especially for long-term forecasts that are strongly affected by external factors not represented in historical price data.

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