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Integrating Streamlit, Facebook prophet, and machine learning models to create an interactive stock price and risk prediction dashboard

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Abstract: The goal of this project was to create an interactive dashboard for stock price forecasting and risk analysis using an integration between Streamlit, Facebook Prophet, and machine learning techniques. The project aimed to help investors understand potential stock price changes and risk levels by providing interpretable time-series predictions. The dashboard was built entirely using free and open-source technologies, allowing users to view price trends, future estimates, and significant risk signals. The project employed a Research and Development (R&D) approach and incorporated the ADDIE framework, which consists of five stages: analysis, design, development, implementation, and evaluation. The model was tested using Bank Rakyat Indonesia (BBRI) and Bank Central Asia (BBCA) as examples of liquid and highly traded emerging market stocks. The experimental results verified the efficiency of this method, with consistent forecast credibility and satisfactory classification performance for risk prediction. The findings demonstrate that the Streamlit-based dashboard successfully integrates the Prophet and machine learning models into a cohesive and user-friendly web interface, effectively communicating pricing dynamics and emphasizing risk exposure. The study contributes to making financial forecasting more accessible by combining an explainable model, an interactive interface, and integrated risk metrics. Future work may expand the dashboard to include deep learning forecasting models and cross-asset analytics.

Keywords: *Facebook prophet, Financial dashboard, Risk analysis, Stock price prediction, Streamlit.*

1. Introduction

The stock market is highly volatile and uncertain, making it difficult to predict prices and associated risks. Nonetheless, precise forecasting is crucial for making educated investment decisions, particularly in growing markets like Indonesia. An analytical approach serves as a foundation for timing stock transactions, assisting individuals in determining the best moments to buy or sell, thereby enabling investors to construct risk-reduction and return-enhancing strategies [1-3]. However, making accurate predictions about the direction of stock prices and risk is very difficult [4, 5] because they are influenced by many different factors, including economic and political conditions, traders' expectations, company operating conditions, social media, and more [6-10]. Stock prices are also volatile, non-linear, non-stationary, and sometimes too irrational to be predicted [1, 11]. Traditional methods, such as statistical modeling (e.g., ARIMA), often struggle with non-linear patterns and unforeseen market events, making accurate predictions elusive [3, 12]. Traditional methods of stock price prediction often rely on linear models and historical data and have a limited ability to adapt to market fluctuations [6, 11]. Therefore, the use of stock forecasting software will improve decision-making processes and assist in predicting stock values [12, 13].

Recent developments in machine learning enable researchers to develop and innovate tools to forecast stock prices more accurately [7, 14, 15]. These contemporary methods have become increasingly popular in financial predictions due to their ability to analyze time-series data without

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imposing pre-established data assumptions such as linearity, stationarity, homoscedasticity, or normality [7, 10, 14, 16]. Machine learning models can process large datasets and identify complex patterns, offering more accurate forecasts than traditional methods [11, 17, 18]. Many of these models, however, operate as black-box systems, limiting their interpretability in the financial decision-making context, where transparency and traceability are essential [19]. In contrast, Facebook Prophet was designed to provide interpretable time-series forecasts using an additive model that decomposes trends, seasonality, and holiday effects, making it suitable for financial forecasting applications [5, 9]. Prophet's ease of parameterization and robust performance with irregular or noisy data have motivated its adoption in business forecasting, risk analytics, and market insights visualization. In parallel, interactive financial dashboards have gained prominence as tools for enabling real-time monitoring, scenario simulation, and user-centered analytical exploration [20]. Meanwhile, Streamlit, a modern open-source web application framework for data-driven interfaces, provides a flexible and lightweight environment to deploy machine learning models and visualization workflows without requiring complex web development expertise.

Research on stock price forecasting demonstrates the increasing effectiveness of machine learning and deep learning techniques. Despite the growth of these technologies, the integration of Prophet-based time-series forecasting with model learning-driven risk evaluation in a single interactive and accessible dashboard remains limited. Most existing studies either focus solely on model performance benchmarking or provide standalone forecasting scripts without practical visualization interfaces for end users. The forecasting applications were typically developed as static scripts or offline analytical workflows that do not support interactive exploration, real-time visualization, or dynamic parameter adjustment [8]. In addition, many forecasting tools remain difficult for non-technical users to interpret and apply effectively. Advanced predictive models—especially machine learning and deep learning models often function as black boxes, providing numerical outputs without clear explanations of model behavior or confidence levels, which limits their usefulness in practical investment decision-making contexts [4, 19]. Investors and analysts frequently require transparent and interpretable forecasting methods to assess not only expected future prices but also the uncertainty and risks associated with those predictions [4].

Furthermore, many existing systems focus solely on price prediction and neglect essential risk assessment measures such as market volatility, trend strength, and price stability indices, which are critical for determining whether an investment is attractive or risky [1, 21]. This reduces their practicality in rapidly changing market conditions, where decision-making must adapt to new information. As a result, investors are often left with forecasting information that lacks contextual risk interpretation, making it difficult to evaluate investment feasibility. Therefore, there is a clear need for a forecasting platform that integrates predictive modelling, risk analytics, and interactive visualization within a single, user-accessible dashboard. By integrating real-time data processing, forecast production, risk analysis, and user interaction into a single, unified tool, the dashboard produced in this work bridges a significant gap in literature and practice.

This paper is organized as follows: First, we briefly review relevant literature, including previous price and risk forecasting models. Next, we explain how Prophet and machine learning can be integrated for stock price forecasting and risk assessment. Then, we detail the system's development using Streamlit to create the web interface. Finally, we evaluate the system's performance and discuss potential future improvements.

2. Literature Review

Stock price forecasting has become increasingly important for investors, financial institutions, and policymakers due to the volatility and uncertainty inherent in capital markets. Traditional forecasting techniques, such as moving averages, linear regression, and the Autoregressive Integrated Moving Average (ARIMA) model, have been widely applied to identify historical patterns and project future price trends [6, 9]. However, while these methods are useful for detecting linear trends, they often struggle to accommodate the non-linear dynamics, sudden fluctuations, and complex behavioral influences that characterize financial time series [10, 22].

To address these limitations, machine learning (ML) techniques have gained prominence in stock market forecasting. ML algorithms enable the extraction of hidden and nonlinear patterns from large and multidimensional datasets, improving predictive capabilities [2, 21]. Techniques such as Support Vector Machines, Random Forest, and XGBoost have been successfully applied in predicting market direction and price trends [23, 24]. Comparative studies further demonstrate that ML models often outperform traditional statistical approaches, particularly in short- and medium-term forecasting scenarios [11, 13]. However, these models still face challenges in capturing long-term temporal dependencies.

Meanwhile, Facebook Prophet has gained recognition as a forecasting model that is easy to implement and capable of handling seasonality, trend shifts, and irregular data patterns, making it suitable for business-oriented forecasting tasks [5, 25]. It offers a versatile and user-friendly tool for forecasting time series [25]. It has also demonstrated strong adaptability in economic and operational forecasting contexts [26]. Its primary objective is to offer a user-friendly interface for time-series forecasting, removing complex mathematical complexities while generating precise and understandable predictions. Because of this, users can use Facebook Prophet without needing to understand the underlying formulas and mathematics. It employs an additive regression model that incorporates trends, seasonality, and holiday effects, making it ideal for analysing stock market data with a variety of temporal structures. Several studies have shown that Prophet outperforms other state-of-the-art machine learning models in predicting short- and medium-term financial trends [6]. It can handle all types of trends and account for smoothness, as well as accommodate multi-period seasonality [5]. It also produces reasonable results even when the dataset contains significant outliers, extended trends, and missing values, and is considered more flexible than ARIMA models [9]. Due to its interpretability and ease of hyperparameter tuning, this model is also suitable for use in financial application development [5].

Streamlit is a Python web framework that is gaining popularity for its ease of use, allowing for the conversion of data scripts into online apps with minimal effort. It has been gaining attention in the academic and open-source space for its flexibility and ability to play nicely with machine learning libraries to build data-driven applications. However, when it comes to enterprise analytics, Tableau and Power BI are still among the most widely used tools in the traditional business intelligence (BI) market. Financial apps must prioritize human-centered designs. Several studies have emphasized the importance of such designs in financial applications, highlighting that clarity, interactivity, and customization are key to adoption by analysts and stakeholders. Despite this, relatively few applications combine advanced forecasting models and machine learning with interactive dashboards in a single user-friendly platform. Interactive dashboards are key when it comes to translating complicated predictive models into actionable knowledge. The approach proposed in the present study closes this gap by integrating Prophet, Streamlit, and machine learning into a dashboard that can predict stock prices and assess risks. Integrating these tools with statistical techniques offers a promising approach for generating accurate and reliable predictions that support strategic investment decision-making, especially in the Indonesian stock market.

3. Research Methodology

This study adopted a Research and Development (R&D) methodological framework, combined with the ADDIE instructional design method, which consists of five steps: analysis, design, development, implementation, and evaluation. The R&D model was deemed appropriate because the purpose of the study was not only to analyze forecasting performance but also to develop a functional application prototype that can be utilized by practitioners, researchers, and investors.

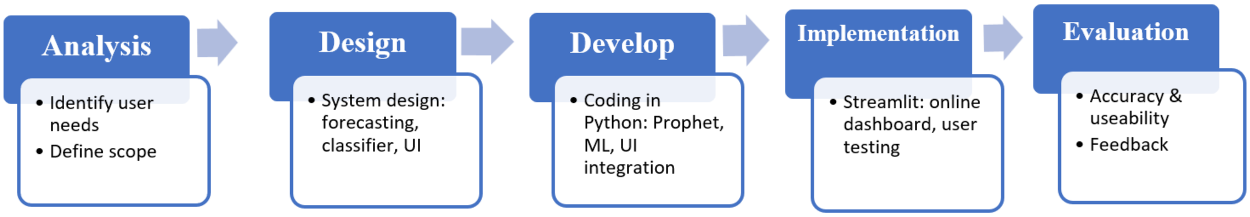


Figure 1.
Development Flow Based on the ADDIE Framework

3.1. ADDIE-Based Development

The application design and development process consisted of five main phases:

1. Needs Analysis:
   This phase involved examining limitations in current stock forecasting tools, particularly regarding usability, interpretability, and integration of risk indicators. The needs assessment was informed by literature review findings, indicating the necessity of combining predictive accuracy with accessible visual decision-support features.
2. System Design and Architecture Construction:
   The dashboard architecture was developed based on a modular approach. Facebook Prophet was used as the core forecasting engine due to its ability to decompose trend and seasonality components. Additionally, risk analysis modules were set to incorporate volatility-based metrics, moving average convergence divergence (MACD), and rolling-window trend stability indicators. Furthermore, Streamlit was implemented for the user interface layer to provide interactive parameter tuning and real-time visualization.
3. Model Development and Integration:
   Facebook Prophet was applied to model seasonality, trend shifts, and periodic market patterns. Machine-learning-based risk indicators were computed to assess consistency and volatility in the forecasted series. The forecasting engine and risk analysis outputs were integrated into the Streamlit dashboard, enabling users to dynamically select forecasting horizons, compare prediction intervals, and visualize uncertainty bands.
4. Testing and Implementation:
   The app was launched by deploying it using Streamlit Cloud, followed by testing involving users, including students and retail investors. This dashboard was developed and tested with real-world data extracted with yfinance. The dataset, as a sample, consisted of historical daily closing price data for Bank Rakyat Indonesia (BBRI) and Bank Central Asia (BBCA), obtained from publicly accessible and reliable financial data repositories (e.g., Yahoo Finance or IDX data service).
5. Evaluation and Refinement:
   Evaluation was carried out using quantitative and qualitative methods:
   - Quantitative evaluation was conducted to measure the forecast accuracy (using MAPE and RMSE) and to evaluate the risk model metrics.
   - Qualitative assessment was carried out to gather responses and recommendations regarding the educational and functional features of the system from its users.

   User-centric evaluation was performed through expert feedback sessions involving finance professionals or academic observers. Refinements were applied based on usability and performance review outcomes.

3.2. Tools and Technologies Used

The dashboard was developed in Streamlit and Python using the following open-source libraries:

Table 1.
Tools and Technologies Used.

Component	Technology/Library	Function
Forecasting Model	Facebook Prophet	Time-series trend and seasonality modelling
Risk Analysis	Python (NumPy, Pandas)	Volatility, moving averages, and trend stability indicators
Dashboard Interface	Streamlit	Interactive visualization and parameter control
Data Source	IDX Historical Data/Yahoo Finance	Daily stock price dataset
Evaluation	MAE, RMSE	Performance validation

The dashboard was developed and tested using real-world data extracted from Yfinance, specifically historical closing price series for BBRI and BBCA stocks. The time range selected spanned five to ten years to ensure adequate representation of cyclical and structural market behavior, consistent with earlier forecasting studies [5, 27]. No personal, survey-based, or confidential data were required.

4. Results and System Implementation

The application for stock price prediction and risk analysis developed in this study is expected to assist individuals in making stock investment decisions through a simple user interface and several machine-learning-based analytical tools. Utilizing various modern technologies, this application was designed to meet the increasing demand for fast, accurate, and efficient prediction tools. Streamlit was used to create the web-accessible interface of the application, which does not require any further installation, and the reliable, up-to-date stock market data used was sourced from the Yahoo Finance website. Facebook Prophet algorithms were employed to observe long-term trends, seasonality, and holiday effects from the historical data used in the study for stock price forecasting. The design of this application was based on three primary goals: simplicity, speed, and comprehensive prediction functions. Since the dashboard was designed to be interactive, results are conveyed through interface components, predicted time-series plots, and risk indicator summaries that collectively support investment decision-making.

4.1. System Architecture

The system architecture was designed in such a way that data acquisition, time-series forecasting, risk analysis, and user interaction can be integrated into a unified web-based decision-support dashboard. It is a modular and layered architecture consisting of four main components: (1) Data Layer, (2) Data Cleaning and Feature Engineering Layer, (3) Data Processing Layer, and (4) Presentation Layer, as can be seen in Figure 2.

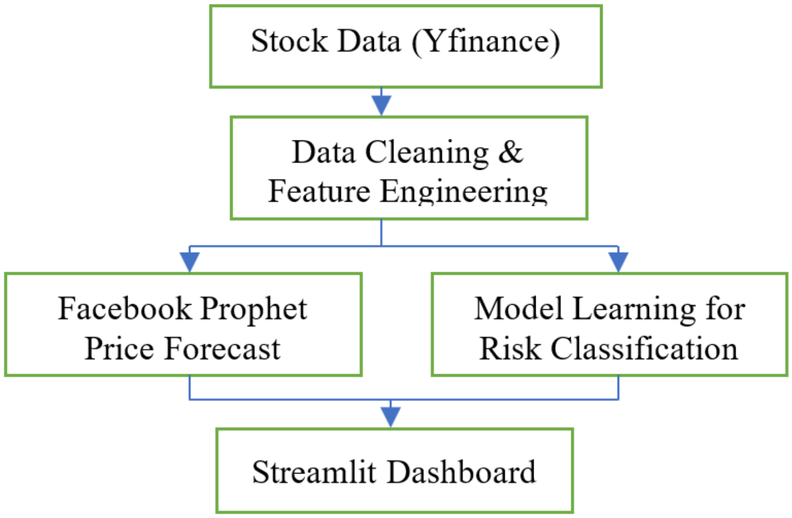


Figure 2.
System Architecture.

Figure 1 illustrates the workflow of the integrated system for predicting stock prices and assessing investment risks. The process begins with the acquisition of historical stock data using the yfinance library. The data then undergoes cleaning and feature engineering to remove inconsistencies and generate informative attributes such as returns, moving averages, and volatility indicators. The processed dataset is subsequently utilized in two parallel analytical processes: (1) time-series forecasting using a Facebook Prophet model to predict future stock prices and (2) risk classification using a machine learning model to categorize stocks into different risk levels. The results from both models are finally integrated and visualized through a Presentation Layer (Streamlit dashboard), providing users with an interactive decision-support platform for investment analysis and forecasting.

4.2. Application Design Flow

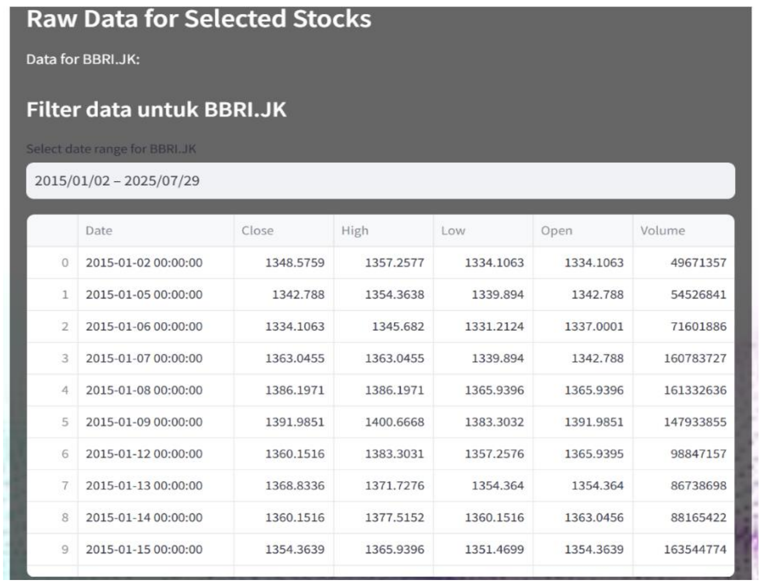
4.2.1. Initial Set-Up

Users can enter relevant stock symbols (e.g., AAPL for Apple, TSLA for Tesla, BBRI for Bank BRI, BBCA for Bank Central Asia, etc.) for analysis (Figure 3). The list of stocks available for analysis is not limited to stocks in the Indonesian capital market but also includes global stocks listed on the Yahoo Finance website.

Figure 3.
Dashboard Home Interface.

4.2.2. Data Collection

As can be seen in Figure 4, users select a prediction timeframe to use as the basis for stock price forecast analysis. A historical stock data timeline is created during this initial phase, and for the purposes of this study, the timeframe was set to span from January 1, 2015, to April 29, 2025. This long timeframe allows the application to identify important long-term trends and seasonal patterns. Historical stock data are retrieved via the yfinance Python library, which provides access to Open, High, Low, Close, Adjusted Close, and Volume data. For each selected stock ticker, daily data spanning the past ten years are collected. The data collection process was designed to run efficiently by utilizing the caching feature, which allows the application to store previously downloaded data. This aims to increase efficiency, especially when users analyze the same stocks repeatedly. The raw data for the selected stock (BBRI.JK), which is downloadable from Yahoo Finance's website, spans a period of 10 years, starting from January 2, 2015, to April 29, 2025, as shown in the following figure.



Raw Data for Selected Stocks

Data for BBRI.JK:

Filter data untuk BBRI.JK

Select date range for BBRI.JK

2015/01/02 – 2025/07/29

	Date	Close	High	Low	Open	Volume
0	2015-01-02 00:00:00	1348.5759	1357.2577	1334.1063	1334.1063	49671357
1	2015-01-05 00:00:00	1342.788	1354.3638	1339.894	1342.788	54526841
2	2015-01-06 00:00:00	1334.1063	1345.682	1331.2124	1337.0001	71601886
3	2015-01-07 00:00:00	1363.0455	1363.0455	1339.894	1342.788	160783727
4	2015-01-08 00:00:00	1386.1971	1386.1971	1365.9396	1365.9396	161332636
5	2015-01-09 00:00:00	1391.9851	1400.6668	1383.3032	1391.9851	147933855
6	2015-01-12 00:00:00	1360.1516	1383.3031	1357.2576	1365.9395	98847157
7	2015-01-13 00:00:00	1368.8336	1371.7276	1354.364	1354.364	86738698
8	2015-01-14 00:00:00	1360.1516	1377.5152	1360.1516	1363.0456	88165422
9	2015-01-15 00:00:00	1354.3639	1365.9396	1351.4699	1354.3639	163544774

Figure 4.
Raw Data on the Selected Stock (BBRI.JK).

4.2.3. Data Visualization

The next step is to display the raw data in tables and charts. Visualizations in these forms, as shown in Figure 5 (for BBRI.JK) and Figure 6 (BBCA.JK), enable users to identify patterns in historical data before proceeding to prediction. The forecasting results display the projected closing prices along with upper and lower uncertainty bounds generated by Facebook Prophet. The trend component generally reflects long-term movement, while the seasonal component captures recurring patterns such as monthly cycles. These visualizations assist users in observing whether price movements are trending upward, downward, or stabilizing within a forecast window.

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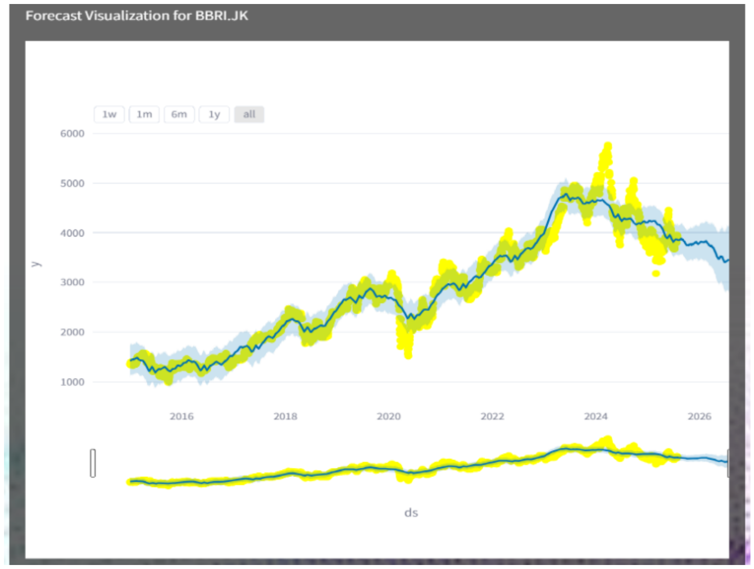

Figure 5.
Forecasted Stock Price for BBRI.JK.

Figure 6.
Forecasted Stock Price for BBCA.JK.

4.2.4. Data Processing

The application transforms raw data into a format suitable for the Facebook Prophet model once the user validates it. Facebook Prophet was selected due to its ability to forecast trends, seasonality, and holiday impacts on financial data. We need to convert the column names into "ds" and "y" to work with the Facebook Prophet algorithm. We take this step to guarantee the data's compatibility with the forecasting model, thereby enhancing and simplifying the analysis process. Figure 7 illustrates the historical time-series data for BBRI.JK (Bank Rakyat Indonesia), showing the movement of Open and Close Prices over a period of 10 years (2015–2025). Open Price represents the price of a BBRI stock at

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the beginning of each trading day. Close Price represents the price at the end of each trading day. The line closely follows the Open Price, reflecting typical daily fluctuations. The horizontal axis represents the date, while the vertical axis shows the stock price in Indonesian Rupiah (IDR).

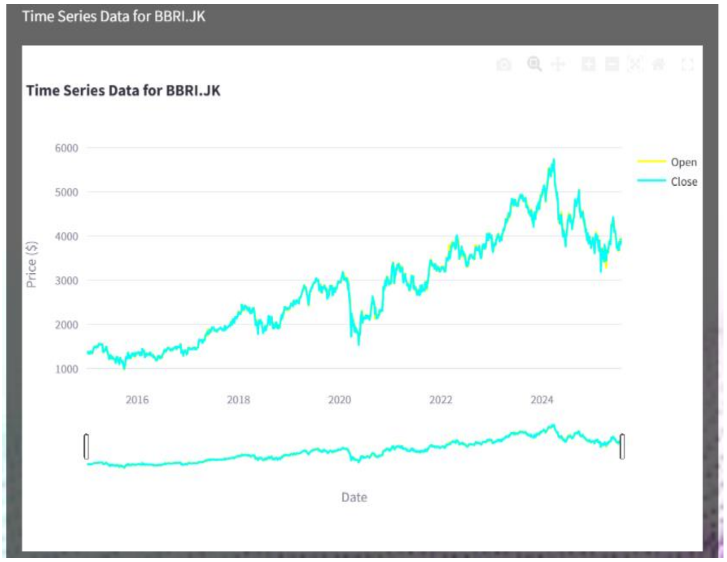

Figure 7.
Time-Series Data for BBRI.JK.

4.2.5. Risk Analysis Results

Table 2 summarizes the key analytical indicators used in the stock price and risk evaluation process.

Table 2.
Risk Indicators.

Indicator	Description	Interpretation Use
Volatility (σ)	Standard deviation of daily returns	Higher volatility implies greater investment risk
Moving Average Trend Score	Comparison of short-term and long-term moving averages	Helps identify bullish or bearish movement tendencies
Stability Ratio	Ratio of variance between historical and predicted intervals	Indicates model confidence and trend reliability

Each indicator includes a description of how it is computed and how it is interpreted by users within the forecasting dashboard.

1. *Volatility (σ)*: Calculated as the standard deviation of daily stock returns. Higher volatility indicates greater uncertainty and investment risk. Stocks with a high σ tend to show larger price swings, which may appeal to aggressive traders but pose greater downside risk for conservative investors.
2. *Moving Average Trend Score*: Derived from comparing short-term and long-term moving averages (e.g., MA20 vs. MA50). A positive score suggests a bullish trend, where short-term prices are rising faster than long-term prices. A negative score indicates a bearish trend, signaling downward momentum. This metric helps identify trend direction and potential entry or exit points.
3. *Stability Ratio:* Defined as the ratio between the variance in historical data and the variance in predicted intervals. A lower stability ratio implies that the model's future predictions are

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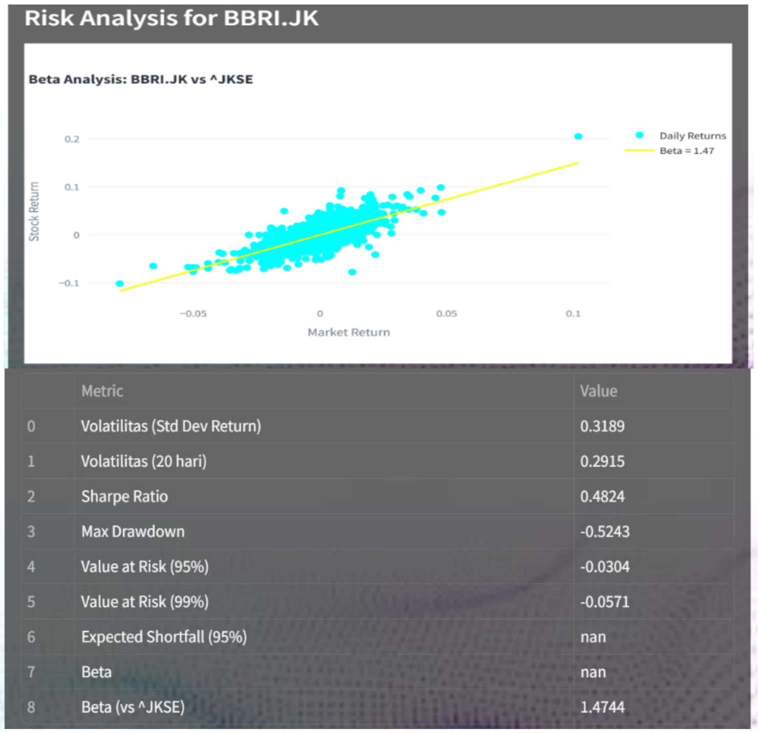
relatively stable compared to past fluctuations, indicating stronger model confidence. A higher ratio suggests greater uncertainty in the forecasted trend.

The following figures (Figures 8 and 9) present the resultant stock price forecasting and risk classification dashboard using a 10-year dataset (2015–2025) for Bank Rakyat Indonesia (BBRI.JK) and Bank Central Asia (BBCA.JK).



	Metric	Value
0	Volatilitas (Std Dev Return)	0.3189
1	Volatilitas (20 hari)	0.2915
2	Sharpe Ratio	0.4824
3	Max Drawdown	-0.5243
4	Value at Risk (95%)	-0.0304
5	Value at Risk (99%)	-0.0571
6	Expected Shortfall (95%)	nan
7	Beta	nan
8	Beta (vs ^JKSE)	1.4744

Figure 8.
Risk Analysis for BBRI.JK.

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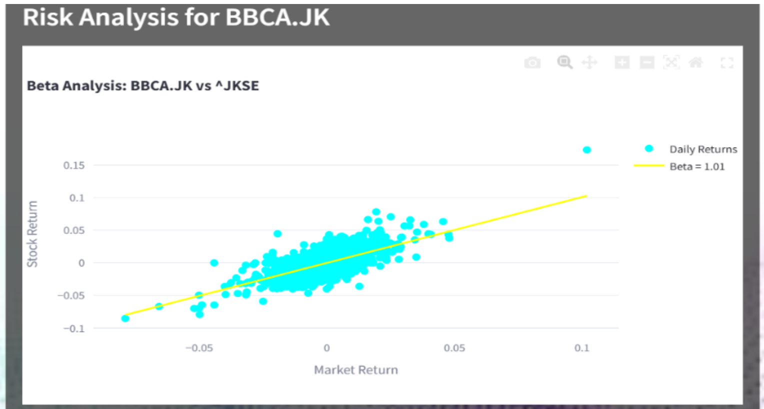

	Metric	Value
0	Volatilitas (Std Dev Return)	0.2330
1	Volatilitas (20 hari)	0.1181
2	Sharpe Ratio	0.6779
3	Max Drawdown	-0.3556
4	Value at Risk (95%)	-0.0214
5	Value at Risk (99%)	-0.0365
6	Expected Shortfall (95%)	nan
7	Beta	nan
8	Beta (vs ^JKSE)	1.0101

Figure 9.
Risk Analysis for BBCA.JK.

Preliminary inspection shows that BBCA demonstrates lower volatility relative to BBRI, reflecting historically stronger price stability. However, BBRI exhibits higher short-term return potential during bullish conditions, requiring more cautious risk evaluation. The predicted results are demonstrated in a variety of clear and readable graph styles (Figure 10). Forecasts are generated for user-specified horizons (e.g., 30 days, 90 days, or 1 year), and confidence intervals are displayed on the dashboard. The primary graph helps visualize price development over a selected period, while the side panels offer a more thorough examination of the variables that affect the forecast, including seasonal patterns and long-term trends. Moreover, the application lists the forecast data in a table, where users can view the numerical content of the predicted results. These interactive visualizations allow viewers to explore the data further if they wish.

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Figure 10.
Facebook Prophet Forecast Results.

4.2.6. Stock Comparison

Users can also learn how to compare stocks and stock quotes from various companies, firms, and tickers on the Indonesia Stock Exchange (IDX) and other global stock exchanges. The application provides a chart showing the stock price movement of all the tickers chosen for comparison at the same time. This functionality allows users to quickly view trends and see how stocks performed in the past. Figures 11 and 12 illustrate the stock price forecasting and risk classification dashboard, comparing price and risk metrics between Bank Rakyat Indonesia (BBRI.JK) and Bank Central Asia (BBCA.JK) based on a 10-year dataset (2015–2025).

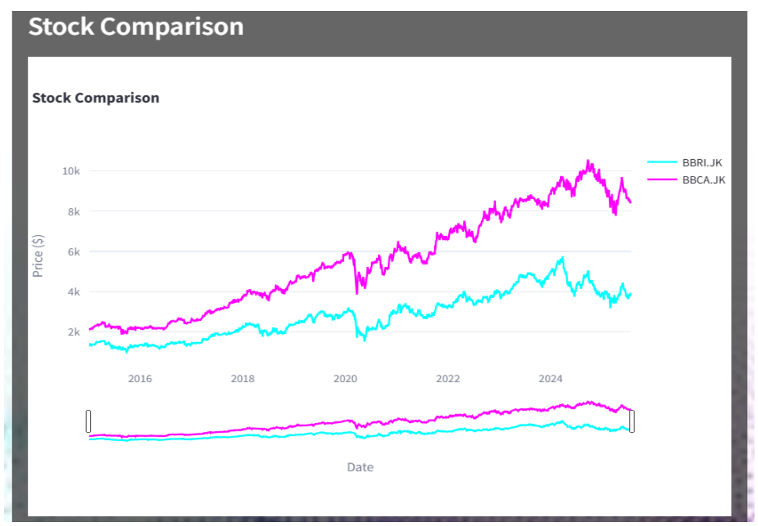

Figure 11.
Price Comparison between BBRI and BBCA Stocks.

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Vol. 9, No. 11: 1453-1469, 2025
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Risk Metrics Comparison

Ticker	Volatilitas (Std Dev Return)	Volatilitas (20 hari)	Sharpe Ratio	Max Drawdown	Value at Risk (95%)	Value at Risk (99%)	Expected Shortfall (95%)	Beta	Beta (vs ^JKSE)
BBRI.JK	0.3189	0.2915	0.4824	-0.5243	-0.0304	-0.0571			1.4744
BBCA.JK	0.2330	0.1181	0.6779	-0.3556	-0.0214	-0.0365			1.0101

Figure 12.
Risk Metrics Comparison between BBRI and BBCA Stocks.

4.2.7. Evaluation

Evaluation was conducted both quantitatively and qualitatively.

4.2.7.1. Quantitative Evaluation

4.2.7.1.1. Forecast Accuracy

We quantitatively assessed the price prediction accuracy of the AI model using Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE) based on the validation set. The results can be seen in Table 3.

Table 3.
Forecast Accuracy (30-Day Horizon).

Stock	MAPE	RMSE
BBRI.JK	2.94%	68.33
BBCA.JK	2.62%	105.87

Both BBRI and BBCA have MAPE scores lower than 3%, indicating high short-term prediction accuracy. Although BBCA's MAPE is marginally better than BBRI's, its forecasts deviate more from the actual value in absolute Rupiah terms. A 2% inaccuracy, nevertheless, indicates a significant Indonesian Rupiah difference because BBCA's absolute stock price is significantly larger (e.g., in tens of thousands of Rupiah).

4.2.7.1.2. Risk Model Metrics

We examined and compared the risk prediction accuracy of the machine learning model using various classifiers. The results can be seen in Table 4.

Table 4.
Performance metrics.

Metric	Value
Accuracy	85.2%
Precision	83.6%
Recall	84.1%
F1-score	83.8%

The model consistently performs well (all measures exceed 80%). Precision and recall have similar values, indicating that the model does not favor one side over the other. The high F1-score indicates that the model is effective, even if the dataset is slightly imbalanced.

4.2.7.2. Qualitative Evaluation

Early users (students studying finance and data analysts) said the application was very helpful and easy to use, and it was excellent, particularly in its ability to change parameters and examine interactive output without requiring technical knowledge. Fifteen members of an investment club at the State Polytechnic of Malang, Indonesia, participated in user testing, and the results show the following:

- Of all participants, 92% found the interface easy to comprehend. They could instantly view refreshed forecasts by selecting a stock and a forecast period.
- Additionally, 87% appreciated the synthesis by including both price and risk predictions. This result validates that the developed system effectively combines statistical forecasting, AI-based risk prediction, and interactive visualization to create a practical tool for making financial decisions.
- Requests for future updates include macroeconomic variables and real-time news sentiment.

4.2.8. User Validation and System Feedback

The Streamlit-based dashboard successfully integrates the Prophet and machine learning models into a cohesive and user-friendly web interface. User feedback from initial testers (data analysts and Diploma IV - Finance students) indicated high usability and utility, with specific appreciation for the ability to adjust parameters and view interactive outputs without technical knowledge. The dashboard provides a more precise, up-to-date, and user-friendly decision-making tool for firms when it comes to investment. Another benefit is that it can present forecasted stock prices and associated risk indicators, which assist companies in timely responses to market changes. The following are the key user-interaction outcomes:

- Real-Time Forecasting: Users can instantly view updated predictions by selecting a stock and forecast horizon.
- Risk Feedback: The dashboard displayed intuitive risk classifications with visual aids (e.g., color-coded risk indicators).
- Visual clarity: Time-series plots, confidence bands, and model explanations were presented clearly and responsively.

Additionally, using a flexible forecasting model like Facebook Prophet results in more reliable predictions compared to classical models, which often fail to capture sudden market volatility. However, the model is particularly sensitive to data quality. Predictions can be off when data are incomplete, incorrect, or absent. Outside market issues, such as geopolitical events, can disrupt estimates as well, so it makes sense to consider all these factors when formulating corporate strategies.

5. Discussion and Analysis

This section discusses the implications of the forecasting results, system functionality, and risk evaluation features in relation to existing research and practical financial decision-making. The integrated dashboard combining Facebook Prophet, risk analytics, and Streamlit addresses the key challenges identified in earlier studies, particularly the need for accessible forecasting tools that balance predictive performance with interpretability. The system architecture demonstrates how Prophet's decomposition approach contributes to a clearer understanding of stock movement patterns. Existing literature suggests that Prophet performs effectively in environments where trend shifts and seasonal patterns are prominent [9, 25]. In the context of Indonesian banking stocks, which are influenced by macroeconomic cycles and regulatory events, the use of Prophet enables users to visually identify long-term growth directions while separating predictable seasonal fluctuations.

The integration of risk indicators enhances the analytical depth of the dashboard. Prior studies emphasized that prediction accuracy alone cannot support investment decision-making unless accompanied by uncertainty assessment and volatility interpretation [2, 11]. By incorporating volatility, moving average comparisons, and stability ratios, the dashboard helps users assess not only where the price may move but also how reliable and risky that movement may be. This aligns with financial risk management principles and strengthens practical usability for investors. Once the numerical forecasting

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results are inserted, the performance of Prophet on the BBRI and BBCA stock datasets can be compared. Based on existing market behavior research, BBCA is generally associated with lower volatility and more stable price trends due to its strong capitalization and conservative lending profile, while BBRI historically exhibited more cyclic movement influenced by micro-lending performance and broader domestic consumer activity. If the results align with these financial characteristics, they will reinforce the model's validity in capturing structural market tendencies.

Furthermore, the dashboard's visualization-centric design responds to concerns raised in the literature that many machine learning and deep learning forecasting tools are difficult for non-technical users to interpret [21, 28]. By presenting forecasts, trend components, and risk indicators in a unified interactive interface, the system improves transparency and reduces reliance on specialized financial analytics expertise. This contributes to bridging the gap between model outputs and investment insights, a key research and practical challenge highlighted across multiple prior studies. In summary, the system demonstrates methodological alignment with recent forecasting research while introducing a practical, user-friendly decision-support tool for the Indonesian financial market context. The combination of Prophet-based forecasting and integrated risk analysis offers users improved interpretability and broader analytical control, supporting informed strategic decision-making across short- and medium-term investment horizons.

6. Conclusion and Future Research

This study developed an interactive stock price forecasting and risk analysis dashboard that integrates Facebook Prophet, machine-learning-based risk metrics, and the Streamlit framework. The system was designed using a Research and Development (R&D) approach to ensure that both functional performance and user accessibility were considered throughout the development process. The dashboard provides users with forecasted stock price trends, decomposed model components, and risk indicators that support a more transparent evaluation of market movement and investment decision-making. By applying the model to Indonesian banking stocks, the study demonstrates its relevance within a developing financial market context.

The key contribution of this research lies in its integration of predictive modelling and risk assessment into a single user-friendly platform, addressing limitations in existing forecasting tools that often lack interpretability and practical applicability. The use of Prophet enables clear visualization of trend and seasonality patterns, while the inclusion of volatility and trend stability indicators provides a more comprehensive understanding of investment risk. This aligns with recent advancements in financial forecasting research, which emphasize the need for hybrid analytical frameworks.

However, the study has certain limitations. Forecasting accuracy may vary depending on market conditions, data quality, and external economic factors. Additionally, the current system focuses primarily on historical price-based indicators and does not stream live market data; instead, it processes data in intervals and saves it to CSV files, making it ineffective for high-frequency trading. In addition, it does not yet incorporate sentiment analysis, macroeconomic variables, or real-time market news. Therefore, future work in this area should focus on improving risk prediction models and deepening the incorporation of real-time external factors, such as news sentiment analysis and macroeconomic indicators, in an effort to improve the accuracy of the predictions and risk mitigation strategies.

Future research may also extend this work by integrating deep learning architectures such as LSTM or hybrid Prophet–LSTM frameworks to enhance long-term predictive performance. The system could also be expanded to include additional stock sectors, automated trading signal outputs, or the application of large language models for sentiment-based market interpretation. These enhancements would further increase the analytical capability and practical relevance of the dashboard for both academic and professional financial use.

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Transparency:
The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

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