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An Explainable Hybrid Learning Model for Stock Price Prediction: Integrating Prophet and Linear Regression in a Web-Based Investment Decision Support System

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Abstract

Stock price prediction remains a challenging problem due to the volatile and nonlinear nature of financial markets. This study developed an explainable hybrid learning model that combined Prophet and Linear Regression, integrated into a web-based investment decision support system. The objectives included designing the hybrid model with technical indicators, evaluating its performance using standard metrics (MAE, MSE, RMSE, and R^2), integrating the model into a user-friendly interface, and assessing usability. A mixed-method approach was adopted, incorporating quantitative techniques (for model development and performance evaluation) and qualitative usability testing. Historical data from five major tech companies (AAPL, MSFT, TSLA, AMZN, and GOOGL) were used alongside indicators like RSI, Daily Return, Volatility, and Bollinger Bands. SHapley Additive exPlanations (SHAP) was employed to interpret the influence of features on predictions. Results showed that the weighted hybrid of Prophet and Linear Regression models outperformed individual models such as Long Short-Term Memory (LSTM), Support Vector Machine (SVM), Prophet, and Linear Regression achieving lower error rates (e.g., MAE of 4.99 and R^2 of 0.83 for AAPL) and improved reliability across multiple stocks. Usability feedback confirmed high user satisfaction, clarity, and trust in the system's predictions and explanations. This study successfully bridged prediction performance and explainability to support better investment decisions.

Keywords: Stock price prediction, Hybrid learning model, Prophet, Linear Regression, SHAP, Explainability, Investment decision support system

INTRODUCTION

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Advancements in Artificial Intelligence (AI) and Information and Communication Technology (ICT) have transformed financial forecasting, enabling rapid data analysis and automation (Samadhiya et al., 2024). Stock price forecasting, however, remains challenging due to market volatility and non-linear data patterns.

Single forecasting models like Support Vector Machine (SVM) and Linear Regression often struggle with the complex, nonlinear dynamics of financial markets, while deep learning models like Long Short-Term Memory (LSTM), may achieve higher accuracy at the cost of interpretability (Ai et al., 2024), (Kurani et al., 2023). Hybrid models combining multiple algorithms offer improved robustness by leveraging complementary strengths (Dostmohammadi et al., 2024).

This study develops an explainable hybrid learning model integrating Prophet and Linear Regression for stock price prediction, deployed in a web-based investment decision support system. The hybrid model is evaluated against Prophet, Linear Regression, LSTM, and SVM to assess comparative performance. The system also uses technical indicators (e.g., Relative Strength Index) and SHapley Additive exPlanations (SHAP) to provide clear explanations of feature influences displayed for user visibility. Predictions are shown in United States Dollar (USD), with an option for Nigerian users to view in NGN, supporting prediction intervals up to 180 days from current day with dynamic charts.

The problem addressed in this study is the lack of transparent, user-friendly forecasting systems and Nigerian localized predictions for US stocks. Objectives include designing the hybrid model, evaluating its performance using quantitative metrics, integrating it into a web platform, and assessing usability. The system empowers retail investors and analysts by providing interpretable forecasting, particularly in Nigeria's financial context.

Stock, often referred to as shares, represents ownership or equity in an organization. The stock market is a platform for buying and selling publicly traded company shares and is divided into the primary and secondary markets. The primary market, which helps to raise capital, consists of the initial sale of securities directly from the organization to investors (Nguyen, 2009). Afterwards investors may choose to resell these shares at mutually agreed-upon prices to other parties. There are several factors that affect stock prices including technical indicators, macroeconomic trends, and market sentiment from news or social media. Stock price prediction is the use of analytical techniques to estimate future stock values based on historical and real-time data (Teixeira & Barbosa, 2025). In financial theory, the Efficient Market Hypothesis states that prices reflect all information, suggesting stock prices are unpredictable. However, data-driven approaches help identify patterns in large datasets aiding more accurate predictions.

Artificial Intelligence (AI) is a field of computer science that creates machines that can perform cognitive tasks such as learning, reasoning, speech recognition, and decision making (Bahoo et al., 2024). It is classified into three main categories: Narrow Artificial intelligence, General Artificial intelligence and Artificial Superintelligence. Narrow AI refers to systems designed to perform a specific task, such as recommendation algorithms or natural language processing tools. General AI aspires to replicate intelligence of humans across a wide range of tasks, whereas Artificial Superintelligence is a hypothetical AI system that would surpass human intelligence in all areas (Macdonald et al., 2023). AI has been widely used to handle complex datasets' features of financial markets, offering a more accurate approach to stock price forecasting as compared to traditional approaches such as technical and fundamental analysis (Sheeba et al., 2023). Machine Learning is a branch of Artificial Intelligence that focuses on creating algorithms and statistical models that allow computer systems to learn from past data, improve, and predict future occurrences without being specifically programmed. There are different categories of machine learning such as supervised, unsupervised and semi-supervised. Supervised learning is where algorithms make use of labeled data to learn relationships between input variable and target results. Examples of this algorithm are regression, decision trees, random forests, and classification models (Khan et al., 2023). Unsupervised learning, however, works with unlabeled data and helps discover unknown patterns and structures. As an example, clustering can be used to group together stocks with similar performances and association analysis might allow the identification of relationship between stock prices and specific economic events (Naeem et al., 2023).

LSTM is a type of Recurrent Neural Network (RNN) designed to overcome the vanishing gradient problem in traditional RNNs, which limits their ability to retain long-term dependencies. It achieves this through three gates: input, forget, and output that regulate information flow within the network (Wu et al., 2022). This structure enables LSTM to capture both short and long term patterns in sequential data, making it particularly effective for time-series tasks like stock price prediction. LSTM models have shown superior performance compared to traditional machine learning algorithms in modeling the complex, dynamic behavior of stock prices (Bathla, 2020).

SHAP is a model interpretation technique based on Shapley values from cooperative game theory. It quantifies each feature's contribution to a model's predictions by treating features as players in a game and distributing the "payout" (prediction) fairly among them (Lamane et al., 2024). A major advantage of SHAP is its additive nature ensuring that the sum of individual feature contributions equals the model output. This allows for both local (individual prediction) and global (overall model behavior) explanations (Pichaiyuth et al., 2023). In stock prediction models, SHAP enhances transparency by identifying which factors like economic indicators, historical prices, or sentiment scores most influence predictions. This interpretability is crucial for validating model behavior and building user trust in AI-driven financial systems (Ojo & Tomy, 2025).

A comparative study on ARIMA, LSTM, and Prophet models for stock price forecasting using Microsoft stock data was conducted (Sunki et al., 2024). These models represent different approaches to time-series prediction: ARIMA modeled linear trends and autoregressive dynamics; LSTM handled nonlinear, long-term dependencies; and Prophet performed best with strong seasonality and trend components. It was noted that no single model consistently outperformed the others, each excelled under specific data conditions. LSTM was most accurate for complex, nonlinear patterns, while Prophet was superior for seasonal trends. Root Mean Squared Error (RMSE) was used as an evaluation metric. The study concluded that hybrid models could leverage the strengths of each, cautioning against a one-size-fits-all approach and recommending model combinations for robust forecasting.

Linear regression remains widely used in stock prediction due to its simplicity, ease of interpretation, and quick computation. It fits a best-fit line to past stock prices to forecast future values. For instance, a Django-based prediction site using linear regression for NIFTY stocks achieved 75–85% accuracy, demonstrating its utility for trend-based forecasting (Antad et al., 2023) However, its inability to capture nonlinear market behavior limits its performance in volatile conditions. Linear regression often serves as a baseline model in comparative studies. Models like Random Forest Regression (RFR) and Support Vector Regression (SVR) generally outperform it due to their ability to model nonlinear patterns and reduce overfitting. According to Panwar et al, (2021), linear regression should be combined with advanced models to balance interpretability and accuracy thereby advocating hybrid systems.

Prophet, developed by Meta, is a robust open-source forecasting tool gaining traction in stock market prediction due to its simplicity, flexibility, and ability to handle missing data while modeling trends, seasonality, and holiday effects. It was used in forecasting Tesla stock and reported effective modeling of seasonal trends and stock upturns, achieving a Mean Absolute Error (MAE) of 15.7. They highlighted Prophet's ease of use and ability to incorporate domain-specific events, such as earnings releases or macroeconomic news. However, its simplified assumptions may limit accuracy during abrupt market shifts (Annapoorna et al., 2024).

To overcome these limitations, hybrid methods like stacking or weighted averaging were proposed. (Kaninde et al., 2022) also compared Prophet with ARIMA and LSTM, finding Prophet faster and less computationally demanding, though slightly less accurate than LSTM in terms of RMSE. Both studies recommended combining Prophet with other models and feature engineering techniques to boost accuracy on complex datasets.

In the attempt to enhance financial time series prediction, LSTM-SimpleRNN Fusion Model for Stock Prediction (Harbaoui &

Elhadjamor, 2024) proposed a hybrid model combining Long Short-Term Memory (LSTM) with Simple Recurrent Neural Networks (SimpleRNN), leveraging Microsoft stock data. The architecture integrates LSTM's long-term memory capabilities with SimpleRNN's responsiveness to short-term fluctuations. This fusion significantly improved predictive accuracy, achieving an RMSE of 0.0138 and Validation MAE of 0.0123 outperforming deep learning baselines like CNN, BiLSTM, and MLP. While the model introduced greater computational demands and required extensive hyperparameter tuning, it demonstrated strong potential for capturing complex temporal patterns. The authors recommended it as a reliable foundation for real-time or hybrid forecasting systems.

In the study Explainable AI Approach Using LSTM and LIME for Stock Price Forecasting (Kumar et al., 2024), Long Short-Term Memory (LSTM) model was used with 14-day timesteps to predict stock prices, capturing complex temporal patterns. To improve interpretability, they applied LIME (Local Interpretable Model-agnostic Explanations) for localized, month-wise insights. Their analysis revealed average closing price as the dominant predictor in 2018–2019, with daily highs and lows also influential.

However, LIME's limitations such as sensitivity to input perturbations, strict local scope, and lack of standardized evaluation metrics raised concerns about explanation stability. The authors recommended exploring alternative XAI methods like SHAP, which provides more globally consistent and theoretically grounded interpretations. Ultimately, they advocated for integrating explainability tools with deep learning to enhance transparency and stakeholder confidence in stock prediction models.

METHODOLOGY

The system is a web-based investment decision support system where users can select a company stock, a duration to view predictions, visualize predictions in form of a graph, and explanations based on SHAP will be provided to clarify why the models prediction were made. Predictions are originally in USD but can be changed to NGN. Users can also compare different stocks using graphs of predicted prices and financial metrics like P/E ratio, Year-over-Year (YoY), Revenue, Beta etc.

Research Design

This study adopts a mixed-method approach, combining quantitative and qualitative methods to address four core objectives: designing a hybrid prediction model, evaluating its relevance, integrating it into a web-based system, and assessing system usability. The quantitative component focuses on developing and evaluating a hybrid model combining Prophet and Linear Regression with SHAP for interpretability using historical stock data and technical indicators. The hybrid model's performance was measured using MAE, MSE, RMSE, and R^2 against standalone Prophet, Linear Regression, LSTM, and SVM models. The qualitative component involves usability testing to evaluate the system's perceived value and ease of use.

Data Collection and Preprocessing

This study uses historical stock market data collected over five years from Yahoo Finance, which is a widely used and reliable source of financial information. The data focuses on five leading technology companies: Tesla (TSLA), Apple (AAPL), Amazon (AMZN), Microsoft (MSFT), and Google (GOOGL). These companies were chosen because of their strong presence in the tech industry and their impact on the stock market. The dataset includes important features such as opening and closing prices, daily highs and lows, trading volume, and the date of each entry.

Before using the data for analysis and model training, several preprocessing steps were carried out to improve its quality and make it suitable for machine learning tasks. First, missing values were handled using forward fill. These approaches help fill in gaps in the data while maintaining the natural flow of the time series. Next, the 'Date' column was converted into a proper datetime format and set as the index of the dataset. This made it easier to perform time-based calculations and organize the data chronologically.

The basic features in the initial dataset are:

1. **Open:** This is the first price at which a stock is sold at the beginning of a trading day
2. **Close:** The last price at which a stock is sold at the end of a trading day.
3. **High:** The highest price a stock is sold on a full trading day.
4. **Low:** The lowest price a stock is sold on a full trading day.
5. **Volume:** The number of stocks sold at the end of a trading day

Exploratory Data Analysis (EDA)

Exploratory Data Analysis was undertaken to investigate the underlying structure, trends, and volatility patterns present in the stock price data. This phase was instrumental in uncovering patterns that could inform feature selection and model development. Boxplots as shown in Figure 1, were employed to assess the distribution and spread of stock prices, facilitating the detection of potential outliers and abnormal price behavior. Additionally, summary statistics as seen in Figure 2, such as mean, minimum, maximum, and standard deviation were computed for key numerical features including opening and closing prices, daily highs and lows, and trading volume. These statistics offered a foundational understanding of the general behavior and dispersion of prices across different companies.

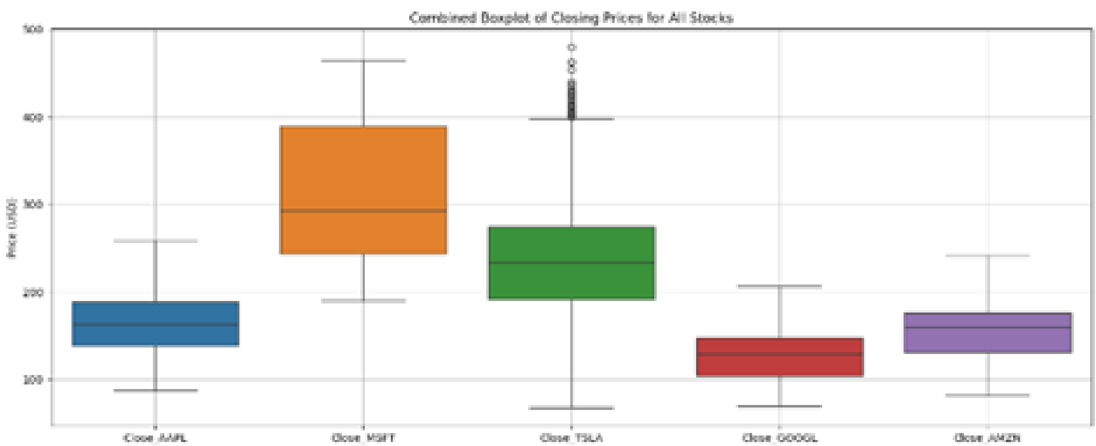

Figure 1. Combined Boxplot of Closing Prices for All Stocks.

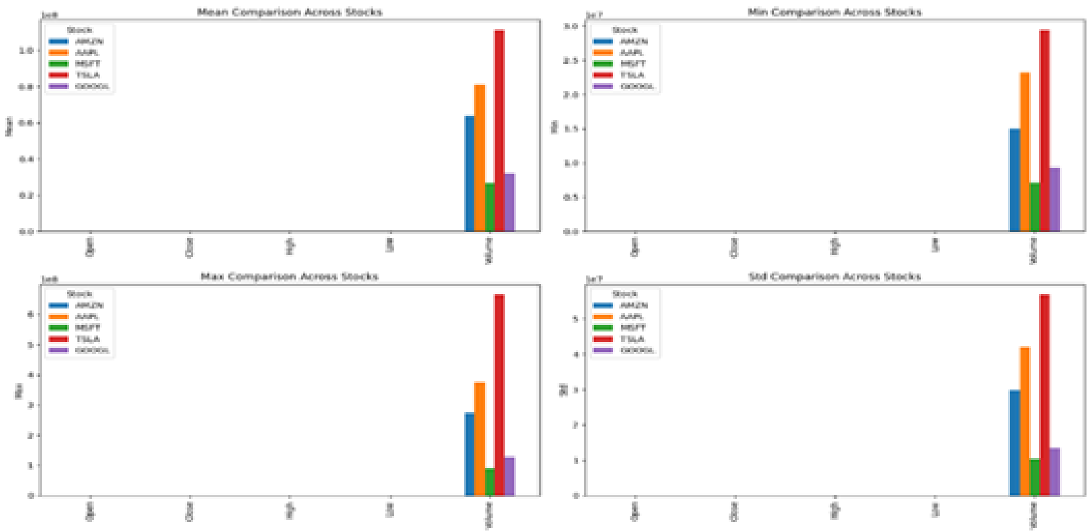

Figure 2. Statistics for All Stocks.

Feature Engineering

The predictive power of the models was enhanced to capture key market characteristics such as trend, volatility, and Daily Return. These features are commonly used in quantitative finance to extract meaningful signals from price movements and were selected based on their relevance to both traditional trading strategies and machine learning inputs. After feature extraction, all variables were normalized using Min-Max scaling to a range of [0,1], which is essential for optimizing the performance of models sensitive to input scales:

$$\text{Min-Max Scaling} = X_{norm} = (X - X_{min}) / (X_{max} - X_{min}) \quad (1)$$

The features were computed as follows (Equations 1-7):

1. **Daily Return:** The daily return quantifies the percentage change in a stock's closing price from one trading day to the next. It captures short-term price movements.

$$\text{Daily Return}_t = ((P_t - P_{(t-1)}) / P_{(t-1)}) \times 100 \quad (2)$$

2. **Volatility:** This reflects the degree of variation in stock returns over a defined window and is crucial for capturing market uncertainty. It was computed using the standard deviation of daily returns over a 14-day window

$$\text{Volatility}_t = \sqrt{1/14 \sum_{(i=t-13)}^{t} (\text{Return}_i - \text{Return}_{mean})^2} \quad (3)$$

3. **Simple Moving Average (MA20):** A 20-day SMA used to capture short-term trends.

$$MA_{20} = (1/20) \sum_{(i=0)}^{19} P_i \quad (4)$$

4. **Relative Strength Index (RSI):** The RSI is a momentum oscillator that assesses whether a stock is overbought or oversold over 14 days. RSI values above 70 typically indicate overbought conditions, while values below 30 suggest oversold conditions.

$$RSI = 100 - (100 / (1 + (\text{Average Gain} / \text{Average Loss}))) \quad (5)$$

5. **Bollinger Bands:** This consists of an upper and lower band around a 20-day SMA, representing volatility-based dynamic support and resistance levels:

Bollinger Upper (BB Upper)

$$\text{BB Upper} = MA_{20} + (2 \times \sigma_{20}) \quad (6)$$

Bollinger Lower (BB Lower)

$$\text{BB Lower} = MA_{20} - (2 \times \sigma_{20}) \quad (7)$$

System Architecture

The web-based investment decision support system is composed of three major layers: the user interface, prediction engine, and backend infrastructure. Each component as listed below plays a key role in delivering explainable stock price forecasts based on historical data and technical indicators.

1. **User Interface (UI):** Developed using Streamlit, the interface allows users to select company stocks, choose prediction intervals (up to 180 days), and visualize predicted prices, company information, and SHAP-based explanations. Interactive graphs powered by Plotly offer dynamic visualization, while the UI supports multi-stock comparisons and currency conversion to Naira (NGN).
2. **Prediction Engine:** At the core is a hybrid machine learning model that combines Prophet and Linear Regression. The model is designed to handle trend and seasonality effectively while maintaining interpretability. SHAP (Shapley Additive Explanations) is integrated to explain each prediction's feature contributions, enhancing transparency and user trust. In addition to the hybrid model, standalone Prophet, Linear Regression, LSTM, and SVM models were trained for benchmarking purposes.
3. **Backend & SQLite Database:** The backend, implemented in Python, manages data preprocessing, model inference, and SHAP explanation generation. All user-selected predictions and associated outputs (e.g., predicted prices, company info, and SHAP values) are stored in an SQLite database. This ensures persistence, fast retrieval, and organized access to previously generated results.

Model Architecture

The overall architecture of the proposed explainable hybrid learning model is designed to support interpretable stock price forecasting within a web-based investment decision support system. The model integrates historical stock price data and multiple technical indicators, which are processed through a hybrid prediction engine that combines time-series modeling and feature-based learning. This architectural design enables the system to effectively capture trend, seasonality, and linear relationships while maintaining transparency through explainability mechanisms. The complete architecture of the proposed hybrid model is illustrated in Figure 3.

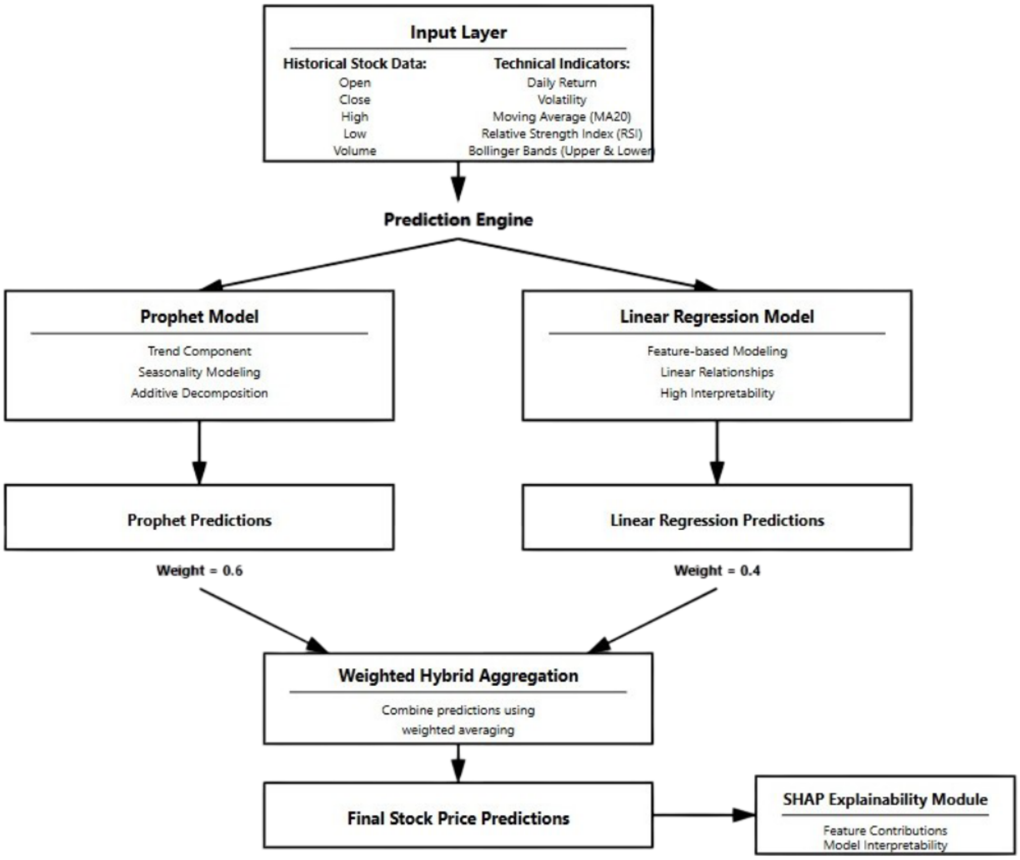

Figure 3. Architecture of the Explainable Hybrid Learning Model.

As shown in Figure 3, the architecture consists of three major components: the input layer, the prediction engine, and the explainability module. The input layer aggregates historical stock data, including open, close, high, low, and volume, alongside derived technical indicators such as daily return, volatility, moving average (MA20), RSI, and Bollinger Bands. These features provide comprehensive market information required for forecasting.

The prediction engine employs a hybrid learning approach by running two models in parallel: the Prophet model and a Linear Regression model. Predictions from both models are combined using a weighted aggregation strategy. The weights assigned to Prophet (0.6) and Linear Regression (0.4) were selected empirically based on validation performance, as Prophet consistently exhibited slightly higher predictive accuracy across most stocks. Assigning a higher weight to Prophet therefore improved overall forecast reliability while retaining the interpretability benefits of Linear Regression.

To enhance transparency and user trust, the final predictions are passed to a SHAP explainability module, which quantifies the contribution of each input feature to the predicted output.

System Usability Evaluation

To evaluate the usability of the web-based investment decision system, a structured feedback form as shown in Table I was used to collect quantitative data from users. The form included a series of rating-scale questions (from 1 = very poor to 5 = excellent) assessing key usability aspects such as system responsiveness, ease of navigation, clarity of information presented, useful predictions and explanations, and overall user satisfaction. The survey was distributed to a group of target users after they had interacted with the system. Responses were collected electronically and analyzed using basic statistical methods.

Table 1. Usability Testing Questionnaire.

Questions	1 (Very Poor)	2 (Poor)	3 (Average)	4 (Good)	5
1. The system loaded predictions quickly when I selected a stock or number of days	☐	☐	☐	☐	☐
2. Navigating through the system was straightforward	☐	☐	☐	☐	☐
3. The design of the graphs showing the predicted prices were clear	☐	☐	☐	☐	☐
4. The stock price predictions were useful in making investment decisions	☐	☐	☐	☐	☐
5. The system's explanations increased my understanding of how stock prices are influenced	☐	☐	☐	☐	☐
6. I trust the predictions provided by the system	☐	☐	☐	☐	☐
7. The stock comparison was useful in making investment decisions	☐	☐	☐	☐	☐
8. The system has all the functions and capabilities I expect it to have	☐	☐	☐	☐	☐
9. I would recommend this system to other investors	☐	☐	☐	☐	☐
10. Overall, I am satisfied with the system	☐	☐	☐	☐	☐

RESULTS

Theoretical Framework

A theoretical framework outlines the structure and concepts guiding the design of a model. In this study, it defines how historical stock data and technical indicators are used to predict prices through a hybrid of Prophet and Linear Regression. Prophet captures trends and seasonality, while Linear Regression models linear relationships. Weighted outputs (0.6 Prophet, 0.4 Linear Regression) are combined based on validation metrics. SHAP ensures interpretability by explaining each feature's contribution to predictions. Figure 4 illustrates the framework.

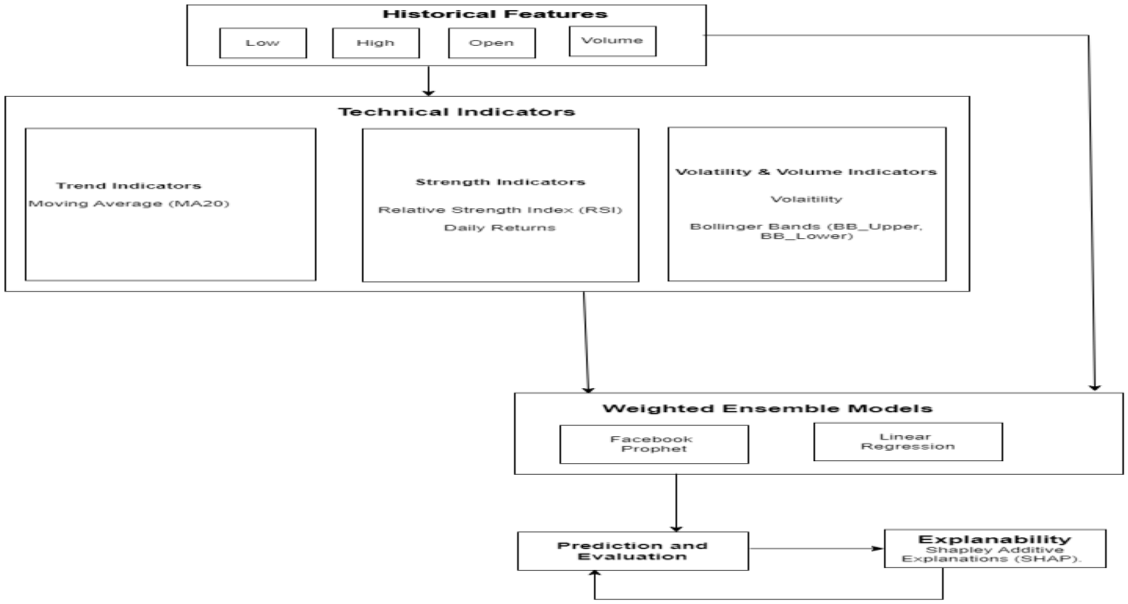

Figure 4. Theoretical Framework of the system.

Model Evaluation

The model's performance was evaluated using quantitative metrics: MAE, MSE, RMSE, and R^2. The dataset was split chronologically (80% training, 20% testing), with 20% training data reserved for validation. The hybrid model was compared against standalone Prophet, Linear Regression, LSTM, and SVM, as shown in Tables 2-6.

Table 2. Apple's Metrics (AAPL).

Model	MAE	MSE	RMSE	R^2
Stacking Hybrid	6.98	49.45	7.03	0.82
Weighted Hybrid	4.99	25.60	5.06	0.83
Prophet	5.92	36.01	6.02	0.80
Linear Regression	7.40	56.52	7.51	0.70
LSTM	10.69	148.10	12.17	0.69
SVM	10.54	237.36	15.41	0.67

Table 3. Microsoft's Metrics (MSFT).

Model	MAE	MSE	RMSE	R^2
Stacking Hybrid	8.67	86.43	9.30	0.83
Weighted Hybrid	7.29	61.24	7.83	0.84
Prophet	6.41	48.12	6.94	0.81
Linear Regression	8.76	82.14	9.06	0.80
LSTM	10.79	154.51	12.43	0.72
SVM	19.34	764.77	27.65	0.56

Table 4. Tesla's Metrics (TSLA).

Model	MAE	MSE	RMSE	R^2
Stacking Hybrid	7.12	63.45	7.97	0.82
Weighted Hybrid	5.87	42.18	6.49	0.83
Prophet	6.45	54.32	7.37	0.82
Linear Regression	8.23	78.91	8.88	0.70
LSTM	15.69	426.20	20.65	0.73
SVM	19.58	1046.55	32.35	0.60

Table 5. Amazon's Metrics (AMZN).

Model	MAE	MSE	RMSE	R^2
Stacking Hybrid	6.24	51.87	7.20	0.84
Weighted Hybrid	5.18	35.64	5.97	0.85
Prophet	4.87	28.45	5.33	0.84
Linear Regression	7.34	62.18	7.89	0.81
LSTM	8.91	114.88	10.72	0.68
SVM	8.57	147.70	12.15	0.59

Table 6. Google's Metrics (GOOGL).

Model	MAE	MSE	RMSE	R^2
Stacking Hybrid	7.45	68.92	8.30	0.84
Weighted Hybrid	6.32	51.23	7.16	0.86
Prophet	6.78	58.14	7.63	0.81
Linear Regression	9.12	95.47	9.77	0.79
LSTM	10.91	134.88	11.62	0.45
SVM	12.34	186.54	13.66	0.27

1. **Model Evaluation:** Across all five technology stocks, the Weighted Hybrid model generally outperformed individual models, achieving MAE values ranging from 4.99 to 7.29 and R^2 values above 0.80. Comparisons with standalone Prophet, Linear Regression, LSTM, and SVM (Tables 2-6) confirm that combining trend modeling and linear regression improves prediction accuracy and reliability

Table 7. Usability Questionnaire Feedback.

Usability Dimension	Average Score (1–5)
Prediction Speed	4.54
Ease of Navigation	4.38
Graph Clarity	4.45
Usefulness of Prediction	4.23
Explanation of Predictions	4.54
Trust in Prediction	4.27
Stock Comparison Feature	4.31
System Capabilities	4.18
Recommendation to Others	4.64
Overall Satisfaction	4.62

2. **Usability Questionnaire Feedback:** Usability feedback (Table 7) indicates high user satisfaction across all evaluated dimensions, with average scores exceeding 4.2/5. Users particularly valued the clarity of predictions and explanations, as well as the stock comparison feature.

3. **Stock Prediction Module:** This page is where the user can select a stock symbol, duration to see predictions and get a graph showing 90 days of actual vs predicted stock prices along with the prediction for the selected number of days.

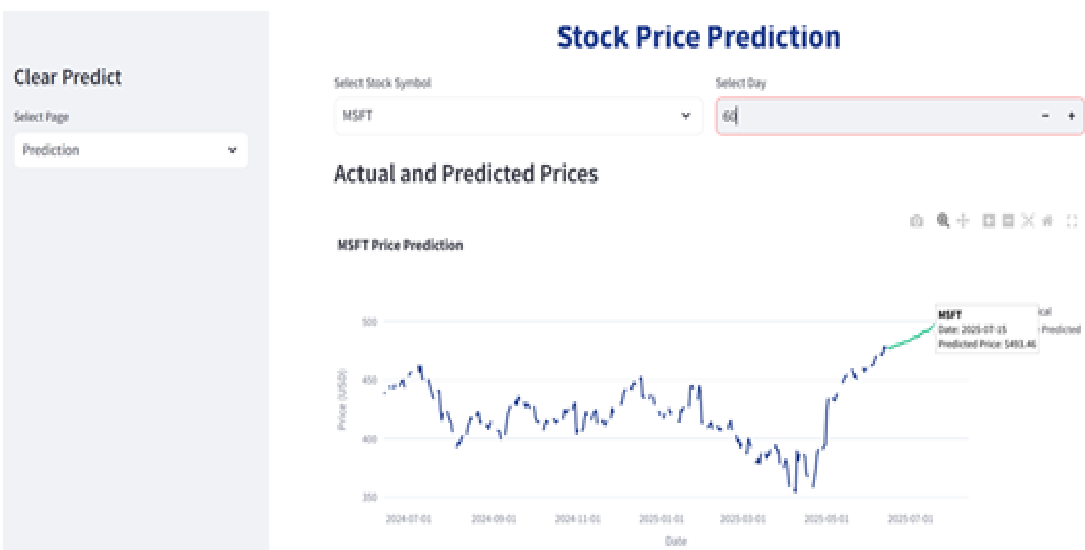

Figure 5. Stock Prediction Module (60 days prediction for Microsoft in USD).

Figure 6. Stock Prediction Module (60 days prediction for Amazon in NGN).


Price Change Explanation

On 2025-06-18, AAPL's price is expected to rise by 0.33%, driven by: Previous Day Close (197.97) increased the price by $0.57.; Bollinger Band Upper (204.90) increased the price by $0.03.; Opening Price (197.64) increased the price by $0.02.; 20-Day Moving Average (200.23)

Figure 7. Price Change Explanation.

4. **Stock Comparison Module:** The stock comparison module, illustrated in Figure 8, enables users to visually compare the predicted prices of multiple companies over a selected period. This feature assists investors in making Informed decisions by analysing price trends across different companies on the same graph. Each stock is color-coded, and interactive plots allow users to focus on specific companies.

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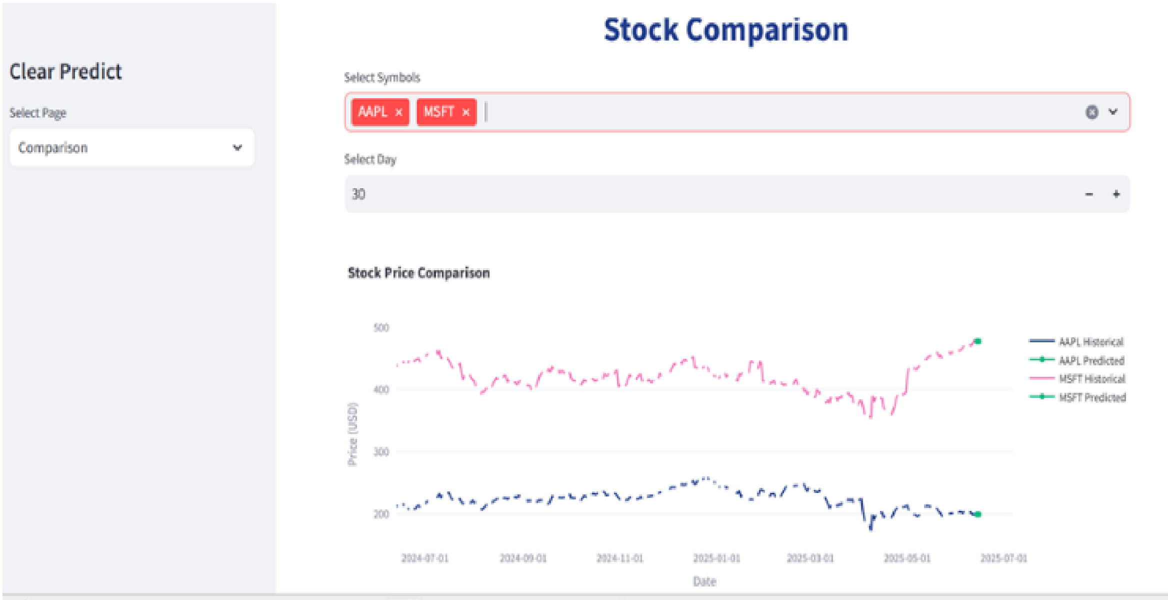

Figure 8. Stock Comparison Module using graphs (Apple and Microsoft).

DISCUSSION

The results demonstrate that the proposed weighted hybrid model combining Prophet and Linear Regression generally achieved superior performance compared to standalone Prophet, Linear Regression, LSTM, and SVM models across all evaluated stocks. As shown in Tables 2-6, the hybrid model consistently recorded lower error values and higher R^2 scores, confirming that combining complementary models improves forecasting accuracy and stability. This finding aligns with existing studies that reported improved robustness and predictive performance from hybrid and ensemble approaches in financial time-series forecasting (Dostmohammadi et al., 2024), (Sunki et al., 2024), (Kaninde et al., 2022).

While deep learning models like LSTM have been shown to model nonlinear market behavior effectively (Wu et al., 2022), (Bathla, 2020), their performance in this study was inferior to the hybrid model, likely due to higher data and tuning requirements, as also noted in prior comparative analyses (Kurani et al., 2023), (Khan et al., 2023). Unlike complex deep learning hybrids that achieve high accuracy at the cost of interpretability and computational overhead (Harbaoui & Elhadjamor, 2024), the proposed model maintains transparency and efficiency.

The integration of SHapley Additive exPlanations (SHAP) further strengthens the contribution of this study by providing consistent and reliable feature-level explanations. These addresses limitations identified in earlier explainable approaches such as LIME, which suffer from instability and limited global interpretability (Kumar et al., 2024). The explainability results align with recent studies emphasizing the importance of transparent AI models in financial decision-making systems (Lamane et al., 2024) -(Ojo & Tomy, 2025).

Overall, the findings align with the study's objectives by demonstrating that the proposed hybrid model improves prediction accuracy, maintains interpretability, and supports usability within a web-based investment decision support system. By combining performance, explainability, and user-centered design, this study contributes a practical and transparent forecasting solution for informed investment decision-making.

CONCLUSION

This study developed an explainable hybrid learning model for stock price prediction, integrated into a web-based investment decision support system. The model combined Prophet and Linear Regression in a weighted hybrid to improve prediction accuracy and maintain interpretability. Key technical indicators such as RSI, Daily Return, and Moving Averages were used as input features to enhance the model's learning process. The model was trained using historical data from five major technology companies: Apple, Microsoft, Tesla, Amazon, and Google collected via Yahoo Finance. Evaluation metrics such as MAE, MSE, RMSE, and R^2 showed that the hybrid model outperformed individual baseline models in most cases.

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Data Availability

No new data were generated or analyzed in this study. All data supporting this study are drawn from public repositories and previously published articles cited within the manuscript.

Authors' Contributions

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Competing Interests

The authors declare that there are no competing interests.

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