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Predicting stock market index prices using Facebook Prophet and XGBoost: evidence from the Saudi stock market

KHLEDJ meryem*	MANSOURI hadjmoussa	Borgi Hela
meryem.khledj@univ-tam.dz	mansouri.hm@univ-tam.dz	haborgi@pnu.edu.sa
University of Tamanrasset (Algeria)	University of Tamanrasset (Algeria)	Princess Nourah bint Abdulrahman University (Saudi Arabia)

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Abstract:

This study investigates the effectiveness of two machine learning models—Facebook Prophet and XGBoost—in predicting the Saudi Stock Market Index (TASI). The study relied on a daily series of prices during the post-COVID-19 recovery period. The results reveal that there is a difference in prediction accuracy, as the XGBoost model outperformed the Facebook Prophet model in various accuracy criteria (MSE, RMSE, and MAPE). The study concludes that integrating the strengths of both models can enhance stock index forecasting accuracy, providing valuable insights for financial analysts and policymakers.

Key words: Facebook Prophet, XGBoost, Predict, Saudi stock market.
JEL Classification Codes: C45, C53, G17.

*Corresponding author

1. Introduction

The share marketplace is an essential financial market in free-choice economies that pulls millions of investors and firms looking for earnings. With the advancement of computing technologies and digital trading platforms, financial markets have become increasingly dynamic and complex (Yun et al., 2021). In the stock market, players can trade financial instruments and raise capital in a reliable controlled environment. Today's market movements are shaped not only by economic fundamentals but also by political and psychological factors (Caparrini et al., 2024).

An unpredictable stock market makes it difficult for investors to get returns. Traditional methods such as fundamental analysis and technical analysis have limitations due to lagging indicators and imprecise forecasts. Consequently, machine learning (ML) and deep learning (DL) models have gained traction for real-time market prediction, portfolio optimization, algorithmic trading, and risk assessment (Sonkavde et al., 2023). According to Aytaç (2021), predicting future values with a minimal error term is done using time series forecasting techniques in assorted sectors including financial markets. Facebook Prophet comes in as a handy tool through its employment of stochastic models. The FBProphet model is a widely used time series analysis model used for predicting future events such as COVID-19 cases, traffic density, currency movements, tourism demand, and cryptocurrency prices (AKER, 2022). In addition, Prophet is robust to missing data and shifts in the trend, and typically handles outliers well (Saldivar & Ortiz, 2019). According Kaninde et al. (2022), analyzing trends over the past few years can be useful for maximizing profit and minimizing losses in stock market prediction.

Machine learning algorithms like Random Forest, Support Vector Machines, generative probabilistic models, Extreme Gradient Boosting (XGBoost), and parameter optimization techniques are popular for stock market prediction due to their effectiveness and simplicity (Dezhkam & Manzuri 2023). According to Petropoulos and Siakoulis (2023), XGBoost is a tree-based boosting algorithm that enhances Random Forest method, a popular machine learning method. It combines multiple datasets, trees, and bootstrap aggregation, approach to capture non-linearities and perform pattern recognition. Guerra et al. (2022), confirmed that with gradient boosting as its core technique, XGBoost uses a differentiable loss function and optimizes it with a gradient descent algorithm to build an ensemble of classification trees.

Research conducted by Mst Noorunnahar et al. (2023) revealed that the ARIMA and XGBoost models were used for forecasting Bangladeshi rice production, with XGBoost exceeding ARIMA in terms of short-term forecast accuracy. The study highlighted the potential application of these models by the government and development practitioners. Besides, Żbikowski and Antosiuk (2021) compared the performance of logistic regression, SVM, and XGBoost algorithms in predicting the growth of businesses based on the Crunchbase dataset. The XGBoost model achieved the lowest error and highest accuracy. In this case, the best model incorporated variables such as a startup's physical location and its operational field (e.g., software or internet services) into the decision tree structure, demonstrating its usefulness in predicting future business success.

Although previous studies have successfully applied Prophet and XGBoost in diverse contexts, ranging from agricultural forecasting to technology-sector predictions, empirical research comparing these two models in the context of the Saudi financial market remains scarce. Most existing studies focus on developed markets or rely on a single model, overlooking the unique structural, regulatory, and behavioral characteristics of emerging markets such as Saudi Arabia, where Vision 2030-driven diversification and post-pandemic recovery have reshaped market dynamics. This study therefore fills this gap by evaluating and comparing the predictive performance of Prophet and XGBoost using daily data from the Tadawul All Share Index (TASI), thereby providing new insights into the applicability of machine learning-based forecasting in Gulf economies. This study used Facebook prophet and XGBoost algorithms, which are powerful tools in the field of machine learning and were used to predict the Saudi stock market index.

The main objective of this study is to assess and compare the forecasting performance of the Facebook Prophet and XGBoost models in predicting the Saudi stock market index. Specifically, the study aims to determine which model provides higher predictive accuracy and to highlight how combining the strengths of both approaches can improve financial forecasting in emerging markets. By achieving this objective, the study contributes to the growing literature on machine learning applications in financial forecasting and provides practical guidance for analysts and investors operating in the Saudi market.

The paper is organized as follows: the problem of prediction is discussed in the first section, which confirms the importance of algorithms in the forecasting process by presenting previous studies that used machine learning, particularly Prophet and

XGBoost. The second section reviews the related literature, the third explains the data and methodology, and the fourth presents the results and discussion. The final section concludes with the prediction outcomes for each model. The purpose of this study is to highlight the importance of using these models to predict market behavior and understand the direction of financial markets.

2. Literature review

Numerous studies have examined different approaches to forecasting stock market indices in various economies. Index forecasting has attracted growing attention from investors because they recognize its importance in decision-making. The existing literature includes an increasing number of studies focusing on the modeling of financial market indicators.

In his research, Ersinet (2021) attempted to forecast Turkey's hazelnut export quantities over 36 months, beginning in June 2020, using the Facebook Prophet algorithm and the Box–Cox power transformation. The algorithm projected more than 500,000 tonnes of hazelnuts between July 2020 and June 2023, showing an upward trend since June 2020. The dataset also exhibited clear seasonality, with monthly variations and a peak in October, resulting from Turkey’s August hazelnut harvest. This strategy could help Türkiye maintain its leading position in the global hazelnut market.

Qixuan (2022) employed four machine learning models to predict Meta Platforms’ stock prices, with Facebook Prophet (including five macroeconomic regressors) performing best, achieving the lowest mean absolute error (14.08259) among the models tested. The study also included NeuralProphet and ARIMA, and the results showed that the inclusion of macroeconomic regression factors can improve forecast accuracy.

According to Suryoday et al. (2019), predicting stock market returns is largely a matter of direction forecasting, which helps minimize errors and reduce investment risk. For this purpose, they built an experimental framework based on Random Forest and XGBoost algorithms to predict whether stock prices would rise or fall relative to previous prices. The method improved forecasts for several companies and relied on technical indicators to predict stock price movements over the medium and long term.

In contrast, Zhan (2023) used the XGBoost algorithm parameters controlled by a GridSearchCV algorithm for prediction of stock prices from daily stock time series data. The findings of the Zhan model suggest that, through proper control of overfitting and underfitting, XGBoost can achieve better model balance and more accurate stock price forecasts. Similarly, Katterbauer et al. (2022) applied the XGBoost method for Sukuk pricing, demonstrating its effectiveness in regression, classification, and ranking tasks, while also addressing bias caused by missing data.

The study by Toochaei and Moeini (2023), examined the relationship between macroeconomic fundamentals and stock returns in inflation-affected Iran. A multiclass classification model was developed, comparing boosting and bagging approaches. XGBoost achieved the best predictive performance, while AdaBoost produced the weakest results, indicating that boosting ensembles outperform bagging-based techniques. According to Caparrini et al. (2024), XGBoost also performed significantly better than Random Forest and decision trees models in terms of classification accuracy and financial performance. This finding is consistent with the general view that incremental tree-growth methods perform strongly in machine learning competitions and in recent studies applying classification algorithms to financial data.

Overall, the reviewed studies confirm that XGBoost and Prophet have proven effective across different forecasting contexts, yet their comparative performance within emerging markets such as Saudi Arabia remains underexplored. This gap highlights the need for further investigation into how these models can be applied to predict complex and evolving financial indices like the Tadawul All Share Index (TASI).

3. Data and methods

This study investigates the efficiency of the Facebook Prophet and XGBoost models in forecasting the Saudi Stock Exchange Index. It focuses on the evaluation and comparison of the performance of these models to demonstrate their suitability for predicting future TASI movements.

3.1. Data collection

The data used in this research represents the daily closing prices of the Saudi Stock Exchange Index dating from January 3, 2021 to October 30, 2024. This time frame allows us to monitor recent market trends and post-pandemic recovery patterns. The data was obtained from the financial database Investing.com . Each observation corresponds to the closing price of the index on a specific trading day.

3.2. Methodology:

This research employs two distinct forecasting models, which are Facebook Prophet and XGBoost, to predict TASI index prices. The performance of both models is evaluated to determine the most effective approach for forecasting Saudi stock market trends.

3.2.1. Facebook Prophet

Prophet is a time series tool that is useful for studying periodic, trend and holiday effects. It employs piecewise linear functions to represent the trend and Fourier series to describe cycles. In addition, users can specify holidays along with their corresponding days (Li et al 2021). The model is resistant to the effects of missing data, gaps in direction, and extreme outliers (Ibrahim et al. 2021). To capture the trend component in time series data, Prophet typically applies linear or non-linear regression techniques to reveal hidden structures or long-term tendencies (Stefenon et al. 2023). Prophet is built as an additive regression model represented by the following equation:

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

Where g(t) denotes the trend function, s(t) is the seasonal module controlling for seasonal variation, h(t) is the holiday effect, and t is an error term prophet that can be individualized, allowing for conventional time factors and external regressor input. It uses the Fourier series to model different periods and, therefore, works well for periodic effects (Vartholomaios et al. 2021).

3.2.2. XGBoost

The XGBoost framework is a high-performance machine learning framework that uses gradient boosting and decision trees. This format is especially well suited for small to medium sized data sets (Al-Maadid et al., 2022). Parallel processing and regularization involve the benefits of overfitting prevention and prediction accuracy enhancement (Guerra et al., 2022). Similar to Random Forest, it constructs an ensemble of decision trees; however, XGBoost applies a more advanced boosting technique, in which each new model is built to correct the errors made by its predecessors (Petropoulos &Siakoulis, 2021). This iterative learning approach optimizes both the objective function and the model complexity, allowing the algorithm to effectively address overfitting. Although XGBoost offers a wide range of tuning parameters, computational limitations may require the use of simplified optimization techniques such as random search, which can yield results comparable to grid search (Żbikowski &Antosiuk , 2021).

Formally, the model uses K additive functions to predict the output (Goldberg & Mouti, 2022):

$$\hat{y}_{i,t+1} = f(x_{i,t}) = \sum_{k=1}^{K} f_{\mathrm{k}}(x_{i,t}),$$

Where we take $f_k(x) = w_{q(x)}(q{:}\,\mathbb{R}^m \to T, w \in \mathbb{R})$from the space of the regression tree. The function q represents each tree structure that maps a sample of the data set to the corresponding leaf index, T is the number of leaves in the tree, and each f_k is the independent tree structure q and in leaves weight w.

To learn the set of functions in the model. The regularized objective is defined as:

$$\mathcal{L}(f) = \sum_t \sum_i l\left(\hat{y}_{i,t+1}, y_{i,t+1}\right) + \sum_k \Omega(f_k)$$

Where $\Omega(f_k) = \gamma T + \frac{1}{2}\lambda \|w\|^2$

The model is then optimized in an additive manner. If $\hat{y}(t)$ is the prediction for the i-th observation at iteration t-th stage of boosting iteration, then the algorithm adds a new function f_t that minimizes the following objective:

$$\mathcal{L}^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t)$$

The objective function is approximated by a second-order Taylor expansion and and optimized accordingly for details and calculation steps. To prevent overfitting, XGBoost uses shrinkage and feature sub-sampling.

3.2.3. Metrics evaluation

Several error metrics are commonly employed to assess the performance of forecasting models, with Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) being widely used options (Choy et al. 2021). While both are valuable, they possess distinct characteristics. MAE offers a straightforward interpretation, treating all errors equally (Kożuch et al. 2023). Conversely, RMSE penalizes larger errors due to its calculation involving squared error values, making it more sensitive to outliers (Choy et al. 2021). Alongside MAE and RMSE, Mean Absolute Percentage Error (MAPE) is another popular metric, particularly in managerial applications (Usher &Dondio, 2020). MAPE expresses errors as percentages, providing an easily interpretable measure of the average deviation between predicted and actual values (Garlapati et al. 2021).

Three metrics are widely used to assess the performance of time series forecasting models, with the choice based on specific goals and priorities, which are described as follows:

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

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

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

4. Results and discussion

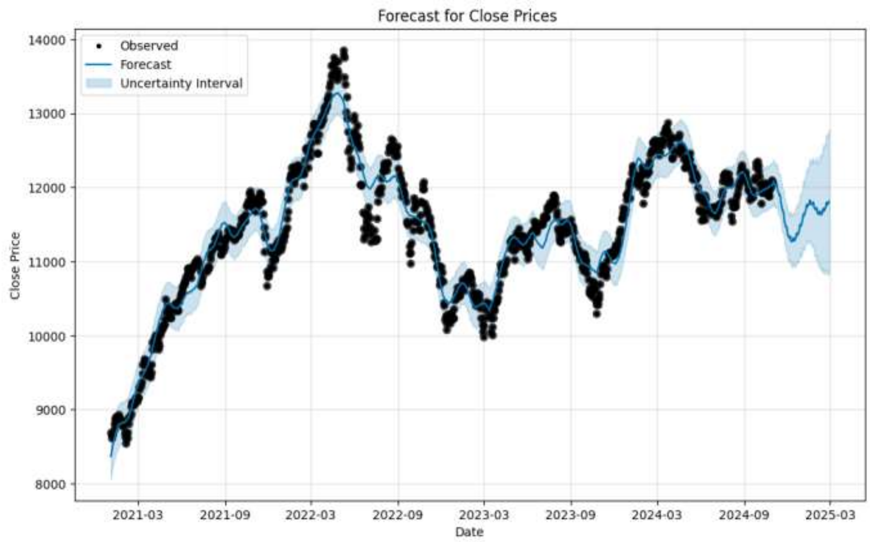
To identify the best model for predicting the Saudi stock index price, a comparison was made between Facebook Prophet and XGBoost. The analytical metrics used in this study were Root Mean Squared Error (RMSE), Mean Squared Error (MSE), and Mean Absolute Percentage Error (MAPE). Lower values of RMSE, MSE, and MAPE indicate higher model accuracy and better forecasting performance.

4.1. Prophet results

The initial one-step-ahead forecast of the Saudi stock index, illustrated in Figure 1, shows that the index prices are expected to rise gradually from 2021 to 2024. The black data points represent the historical index values used to train the Facebook Prophet model, while the blue forecast line indicates the predicted trend. The light-blue confidence intervals reflect the range of prediction uncertainty, extending to 2024.

Overall, the model suggests a steady upward trend in the Saudi stock market during the analyzed period. This projected growth aligns with the broader economic expansion observed in the Kingdom and reflects investor optimism during the post-pandemic recovery phase. However, despite the positive trend, investors should remain cautious about potential market volatility in the long term and consider portfolio diversification as a strategy to manage risk and uncertainty.

Figure 1. *Forecast of Close prices*



Source: Python output

Figure 2, which presents the components of the decomposed time series, provides valuable insights into the behavior of the Saudi stock market index. From 2021 to 2024, the index exhibits a clear upward trend, indicating continuous market growth. This trend may primarily be driven by underlying market forces that exert upward pressure on prices.

Figures 3 and 4 illustrate the characteristic pattern of weekly and yearly seasonality. The weekly component shows that prices tend to reach their lowest point on Mondays and then gradually increase during the rest of the week. This pattern reflects typical investor behavior, as market participants tend to increase buying activity in response to early-week price movements.

The annual component reveals a distinct seasonal cycle, with a noticeable peak in May. This pattern likely reflects cyclical factors and changing market dynamics, possibly influenced by economic conditions, investment cycles, or external environmental factors affecting market behavior.

Figure 2. *Trend of time series*

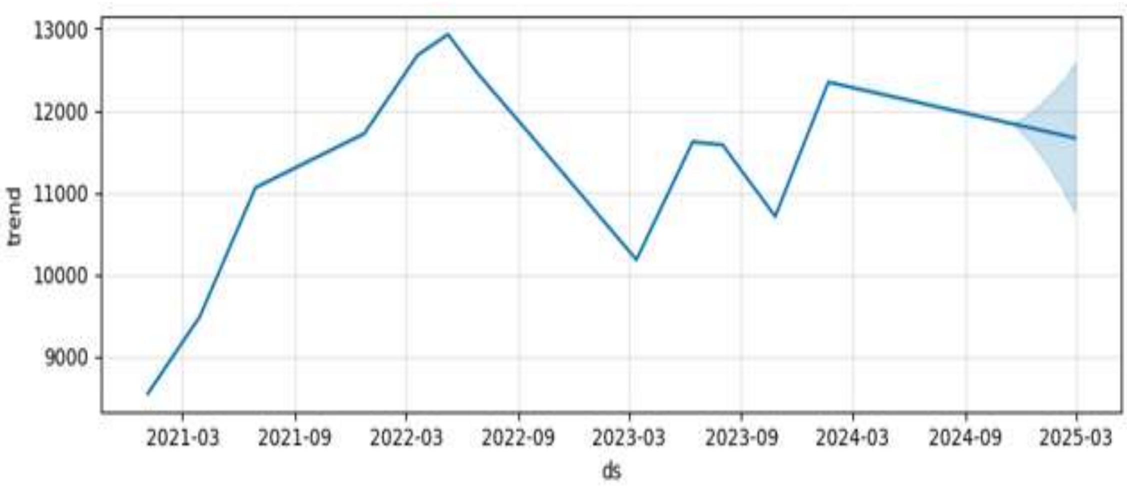


Figure 3. *Weekly seasonality of Prophet*

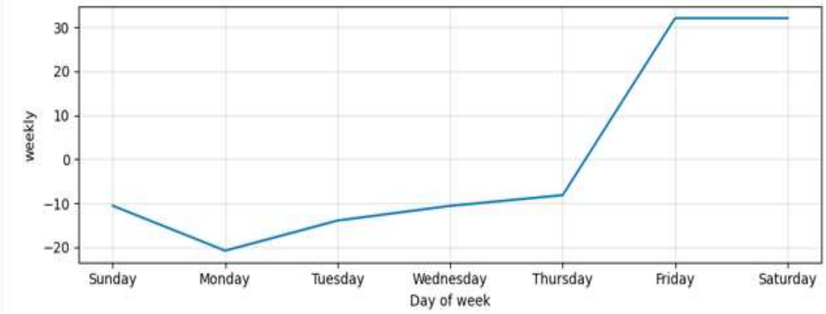
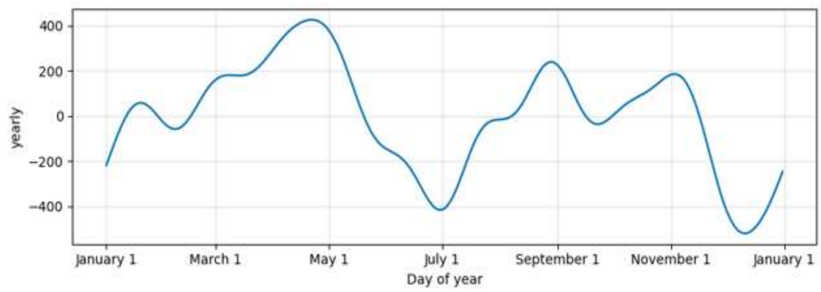


Figure 4. *Yearly seasonality of Prophet*



Source: Python output

4.2. XGBoost results

The XGBoost algorithm relies on a set of hyperparameters that must be carefully tuned to prevent underfitting or overfitting. GridSearchCV is an efficient tuning method that performs an exhaustive search to identify the best-performing combination of parameters. Although this process is time-consuming, it ensures high accuracy and model validity. By systematically evaluating different parameter combinations, GridSearchCV determines the optimal configuration within the defined range, thereby enhancing the overall accuracy and predictive performance of the XGBoost model (Zhang, 2022).

The results of the parameters of the search algorithm are given in Table 1

Table 1. *Parameter Optimization Results*

Best params:	'colsample_bytree': 0.8, 'learning_rate': 0.2, 'max_depth': 3, 'n_estimators': 100, 'subsample': 0.8
Actual Values: fiverandom days	[12158.52, 12122.98, 11786.64, 11890.96, 11697.23]
Predicted Values: five random days	[12030.29, 12176.86, 11953.11, 11932.75, 11583.40]

Source: Own Elaboration based on Python output

The main purpose of this study is to model and evaluate price forecasting models for the Saudi stock market index using Facebook Prophet and XGBoost. The results show a significant difference in forecasting accuracy between the two models, with XGBoost outperforming Facebook Prophet. The XGBoost model achieved the following performance metrics: MAPE = 0.67%, RMSE = 104.24, and MSE = 10,867.75. These results indicate that XGBoost effectively captured the underlying movements of stock prices. The model demonstrated high predictive accuracy due to its ability to identify and model complex non-linear relationships among the features, leading to a more precise representation of market dynamics.

On the other hand, the simpler and more user-friendly Prophet model demonstrated lower predictive accuracy compared to XGBoost. The mean error (MSE) was 50060.53, with an RMSE of 223.74 and a MAPE of 1.51%. Although Prophet successfully captured some of the seasonal and trend patterns in the Saudi stock market data, its overall performance was notably weaker than that of XGBoost.

The significant performance gap observed between the two models highlights XGBoost's strong potential for predicting stock market prices, particularly when dealing with large and complex datasets. However, Prophet remains a valuable tool for understanding long-term trends and seasonal behaviors in financial data.

Both models depend heavily on the quality and quantity of training data; thus, careful attention to data preprocessing and feature engineering is essential. Optimizing these steps can significantly enhance the predictive performance of both algorithms.

Overall, the results offer important insights for financial analysts and investors who apply machine learning techniques to forecast stock price movements. The findings help distinguish the strengths and limitations of each model and guide users in selecting the most appropriate approach. Future research could further improve forecasting performance by integrating Prophet and XGBoost into a hybrid framework, combining their complementary strengths for more accurate and interpretable predictions.

5. Conclusion

This study evaluated and compared the performance of two prominent machine learning models, Facebook Prophet and XGBoost, in forecasting the Saudi stock market index. The results revealed a clear difference in forecasting accuracy, with XGBoost outperforming Prophet across all evaluation metrics (MSE, RMSE, and MAPE). XGBoost achieved higher predictive accuracy because of its ability to model complex non-linear relationships within the data, while Prophet proved useful in identifying long-term trends and seasonal patterns.

This study contributes to the growing literature on machine learning in financial forecasting by providing empirical evidence from the Saudi context. It demonstrates that advanced algorithms such as XGBoost can play a crucial role in improving the accuracy, reliability, and analytical power of forecasting models applied to emerging financial markets.

The findings have important implications for financial analysts, investors, and policymakers in emerging markets such as Saudi Arabia. XGBoost can serve as a reliable tool for short-term forecasting and risk management, supporting more data-driven investment decisions. Prophet, on the other hand, can be used as a complementary model to identify seasonal and structural trends that may inform macroeconomic planning and investment strategies. Integrating such machine learning techniques into financial forecasting systems can enhance predictive capacity, improve market efficiency, and support the country's broader Vision 2030 goals of innovation and digital transformation in the financial sector.

Despite the encouraging results, this study has certain limitations. The analysis relied solely on historical daily closing prices, without considering other influencing variables such as macroeconomic indicators, oil prices, or investor sentiment, which could have an impact on market behavior. The study period (2021–2024) also represents a specific post-pandemic recovery phase, which may not reflect the market's behavior under different economic conditions. Furthermore, model performance could vary when applied to other time frames, sectors, or data frequencies, such as weekly or intraday observations.

Future studies could explore hybrid frameworks that combine Prophet and XGBoost to capitalize on the strengths of both models. Expanding the dataset to include macroeconomic and sentiment variables may also enhance the models' robustness and interpretability. Researchers can further investigate deep learning models, such as LSTM and Transformer architectures, to achieve higher forecasting accuracy. Extending this analysis to other GCC stock markets would allow for comparative insights and a deeper understanding of predictive modeling in regional financial systems.

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