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Barclays Stock Price Prediction Using Advanced ML

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Abstract

Stock price prediction is most intricate issues in financial analytics, demanding high-level methodologies in order to tread the complex relationships between market factors, economic parameters, and investment patterns. Through this study, we investigated how various forecasting models perform in Barclay PLC stock price prediction using LSTM (Long Short-Term Memory), ARIMA (Autoregressive Integrated Moving Average), and Prophet models. Utilizing the historical stock performance data from Yahoo Finance for 2014-2023, we tested every model's predictability through detailed testing and relative comparison.

Our results show that although all models reflect satisfactory forecast accuracy, LSTM universally performs better than the rest with lower error values due to its capacity to identify intricate non-linear relationships in financial time series data. Prophet presents a good balance between accuracy and interpretability, while ARIMA presents an effective baseline method for linear forecasting.

This research adds meaningful insights into financial forecasting methods, illustrating how sophisticated machine learning methods can improve accuracy of stock price forecasting for better investment decision-making.

Contents

1. Introduction

1.1 Overview

Stock markets are a key part of the global economy, providing platforms for investment and helping drive financial growth. Being able to predict stock price movements accurately is important for investors, analysts, and institutions because it helps in making better decisions, managing risks, and improving financial strategies. Stock prices are influenced by many factors, including economic indicators, investor behavior, political events, and company performance, making prediction a challenging but rewarding task. With the advancement of technology, especially in artificial intelligence and machine learning, researchers have been developing better models to improve forecasting accuracy.

Recent studies have looked at combining machine learning techniques with traditional forecasting methods. For example, Zhang et al. (2023) used a hybrid model that combined machine learning and natural language processing to study how news sentiment affects stock prices. Fan et al. (2024) used a pre-trained financial model to predict price movements and found that it performed better than other models with the lowest Mean Squared Error (MSE). Similarly, Ismailova et al. (2024) compared LSTM and GRU models for stock price prediction and found that GRU achieved slightly better accuracy, reaching 99.88% precision.

This project focuses on predicting the stock prices of Barclays PLC, a leading international bank based in London. Barclays offers a range of services, including personal banking, credit cards, corporate and investment banking, and wealth management. Its stock is traded on the London Stock Exchange under the symbol BARC.L, and its share price is closely watched by investors and analysts worldwide. Using historical stock data from 2014 to 2023, this research aims to assess and compare the performance of three forecasting models: LSTM, ARIMA, and Prophet. The goal is to better understand how well these models can predict stock price movements and how they can be used in real-world financial forecasting.

1.2 Research Problem

It is difficult to forecast stock prices because financial markets are complex. Prices are affected by events such as macroeconomic indicators, news, sentiment, and trends. Historical models have difficulty in modeling interactions among these factors. Studies have demonstrated that models such as Prophet perform better than ARIMA, particularly for seasonality, and Holt-Winters performs better than SMA in stock price prediction. Stock markets also exhibit behaviors like trends and volatility, which are challenging to model. Deep learning models like LSTM are able to pick up non-linearity but at a high resource cost. Market fluctuation and quality of data are still a problem in forecasting stock prices.

1.3 Research Question

The core research query underpinning this study is: "What forecasting model out of ARIMA, LSTM, and Prophet is most accurate and reliable in its predictions for the stock prices of Barclays PLC?"

1.4 Aims and Objectives

The overall objective of this study is to design and compare various machine learning models for forecasting Barclays PLC's share prices and assess their performance in terms of accuracy, reliability, and computational cost. Based on a comprehensive comparative study, this research aims to identify the most appropriate model for forecasting Barclays' share prices under different market conditions and for different time horizons. This objective will be fulfilled through the following specific objectives:

1. Data Collection and Preprocessing:

- Gather historical stock price data for Barclays PLC from reputable financial databases.
- Clean and preprocess the data to handle missing values, outliers, and ensure it is suitable for analysis.

2. Model Implementation:

- Develop and fine-tune ARIMA, LSTM, and Prophet models tailored to the dataset.
- Optimize model parameters to enhance forecasting accuracy.

3. Model Evaluation:

- Evaluate how each model performs by applying relevant metrics, including Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE).
- Compare the models to determine which provides the most accurate and reliable forecasts.

4. Result Analysis and Reporting:

- Analyze the forecasting results to draw meaningful conclusions.
- Compile a comprehensive report detailing the methodologies, findings, and implications of the study.

Through these outcomes, this study hopes to generate useful information on the effectiveness of various forecasting methods for the prediction of Barclays stock price, enriching the study of financial forecasting and supporting investors and analysts in making proper judgments. The outcomes will not only be helpful for those particularly interested in Barclays stock but also contribute to stock price prediction methodologies' general knowledge and their application in actual financial analysis.

2. Literature Review

Background

Stock market prediction has been a topic of strong research for many years, originally based on statistical and technical analysis techniques. The Efficient Market Hypothesis (EMH), which was introduced by Fama in 1970, postulates that the stock prices in any market reflect all public information, and it is not possible to obtain consistent results in excess of the market average returns. Many researches challenged this concept, showing that stock markets tend to be inefficient and could be predicted using suitable models. The evolution of models like ARIMA, Prophet, and LSTM to forecast represents an important advancement in computational finance to better understand the movement of stock prices.

Researchers have created sophisticated forecasting models with the advent of machine learning and AI. These models are generally categorized as statistical, machine learning, and deep learning models, each having different strengths. ARIMA continues to be a go-to for linear time-series analysis, while deep learning models such as LSTM perform well in identifying non-linear and sequential patterns, revolutionizing stock market prediction. Box and Jenkins (1976) and Hochreiter and Schmidhuber (1997) proved ARIMA and LSTM to be suitable for stock price prediction, both of which are appropriate for various types of data and needs.

Current research points towards model performance in terms of forecasting stocks. Roy et al. (2023) compared Holt-Winters with SMA and discovered that Holt-Winters excelled with decreased MAPE and improved seasonality modeling. Beneditto et al. (2020) highlighted the better trend and seasonality identification of Prophet than that of ARIMA. Deep learning, particularly LSTM, is on the rise, with Moghar and Hamiche (2020) and Fan et al. (2023) presenting its high accuracy and capacity to process intricate financial data.

Although ARIMA has been a pervasive tool, its linear constraints put a ceiling on its potential to capture stock market volatility. Extensions such as SARIMA and ARIMAX enhance its performance but still stay within linear paradigms. Prophet and LSTM, with their flexibility and non-linear capabilities, hold out promising alternatives for capturing complex stock trends.

T field of stock market prediction has seen rapid development since machine learning and deep learning methodologies emerged. Though even older models like ARIMA remain effective, there are newer technologies such as LSTM and Prophet with better accuracy rates and the power to capture seasonal and non-linear patterns in economic data. These developments offer insightful information concerning the forecasting of stock prices and the foundation of the present project to compare and analyze these models for predicting Barclays' stock price movements.

3. Dataset & Ethics

3.1 Dataset

Historical Barclays PLC stock prices from Yahoo Finance, starting January 1, 2014, to December 31, 2023, form the data employed in this study. The ten-year dataset offers a holistic perspective on Barclays' performance through different market conditions. The dataset consists of daily data with columns including Date, Open, High, Low, Close, Adjusted Close (following corporate actions), and Volume (shares traded). These features provide information on the price action and volume of the stock. Moreover, engineered features such as MA_5 (5-day moving average), MA_10 (10-day moving average), MA_50 (50-day moving average), Daily_Returns (day-over-day percentage change), and Volatility (20-day rolling window standard deviation) were computed to improve the forecasting models by incorporating trends, momentum, and volatility.

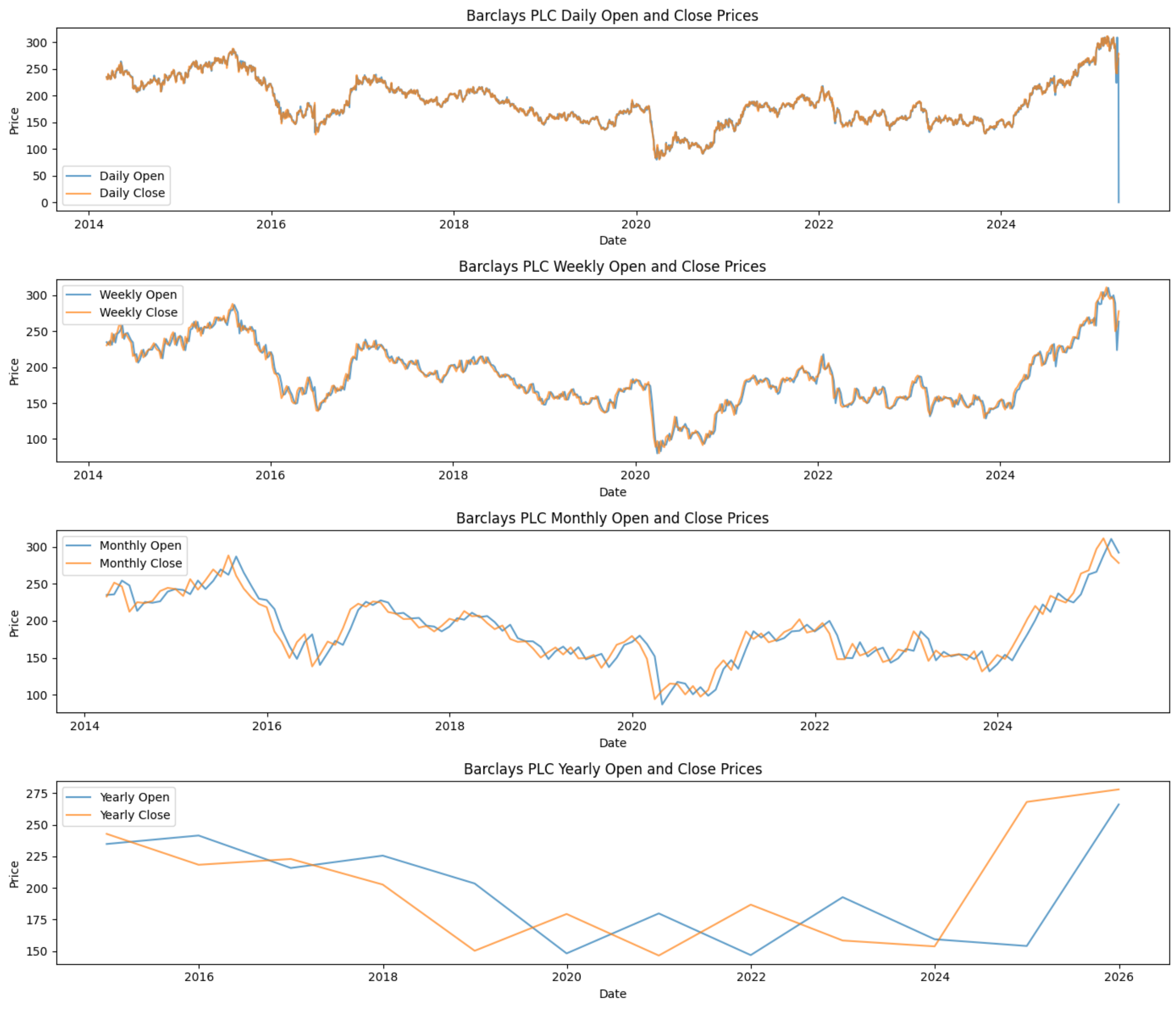

Figure 1: Open and Closing prices for daily, weekly, monthly, and yearly data.

3.1.1 Data Preprocessing

Data preprocessing is used to get the dataset ready for analysis and model training. Some of the key steps in time series forecasting involved filling missing values, usually from non-trading days, via forward-filling or row deletion. Feature scaling via MinMaxScaler was used in LSTM models to provide unbiased feature contribution, whereas ARIMA and Prophet retained the original scale for easier interpretability. Other features such as moving averages (MA_5, MA_10, MA_50), daily returns, and volatility were designed to improve model precision. The data was divided into 80% training and 20% test sets to preserve chronological order and avoid look-ahead bias. Stationarity for ARIMA was tested using the Augmented Dickey-Fuller (ADF) test, and differencing was done if required. For LSTM, sequential data was created with a 60-day window. Finally, Prophet's dataset was reshaped to meet its structural requirements. This process made the strong time series forecasting possible.

3.2 Ethics

This study considers ethical issues surrounding utilization of publicly available financial information and the possible implications of stock price prediction. Information was obtained from Yahoo Finance, where free academic use is permitted and no sensitive personal details are involved, reducing issues of privacy. Proper use and citation and compliance with usage terms were observed. The research focuses on the point that stock price forecasting is inherently uncertain and ought not to determine investment decisions alone; models should be applied together with expert judgment. Ethical standards of fairness, accountability, and transparency guide the methodology and reporting to preclude misuse and ensure responsible utilization, prevent abuse, and enable significant contributions towards financial forecasting.

4. Methodology

4.1 LSTM Model

Long Short-Term Memory (LSTM) networks, developed by Hochreiter and Schmidhuber (1997), are a class of recurrent neural network aimed at identifying long-term dependencies in sequence data and hence used in time series forecasting. As opposed to normal RNNs, LSTMs solve the vanishing gradient problem with an innovative cell state controlled by three gates: forget gate (scales out unnecessary information), input gate (inserts new information), and output gate (regulates output).

The fundamental LSTM operations are:

- Forget Gate: $ft = \sigma(Wf \cdot [ht-1, xt] + bf)$
- Input Gate: $it = \sigma(Wi \cdot [ht-1, xt] + bi)$
- Candidate Cell: $\tilde{C}t = \tanh(WC \cdot [ht-1, xt] + bC)$
- Cell Update: $Ct = ft \cdot Ct-1 + it \cdot \tilde{C}t$
- Output Gate: $ot = \sigma(Wo \cdot [ht-1, xt] + bo)$
- Hidden State: $ht = ot \cdot \tanh(Ct)$

Data Preprocessing for LSTM included cleaning and normalizing features (prices, volume, technical indicators) via MinMaxScaler. Data was put into sequences of 60 trading days with the target being the next day's closing price, using a sliding window strategy. 80% was used for training and 20% for testing, maintaining time order.

Model Architecture and Training employed Keras with TensorFlow backend, consisting of 100 LSTM units with ReLU activation, dropout layers to avoid overfitting, and dense layers for smoothing output. The model was compiled with Adam optimizer and MSE loss, trained for 100 epochs with early stopping and learning rate scheduling. Hyperparameters were optimized using grid search to achieve best performance.

Forecasting and Evaluation entailed making day-ahead forecasts, rescaling outputs, and assessing performance based on MSE, RMSE, MAE, MAPE, and R^2 metrics. Visual plots analyzed predictions against actual prices, and sensitivity analysis conducted tests of varied sequence lengths in order to better model accuracy.

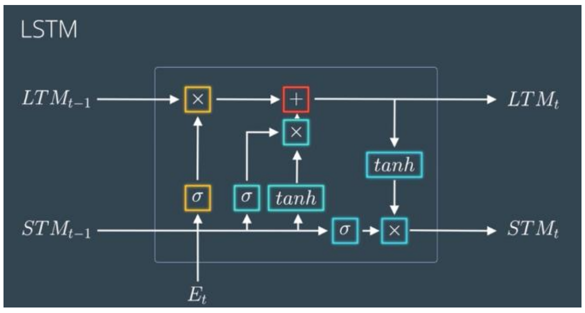

Figure 2: LSTM Architecture (Source)

4.2 ARIMA Model

ARIMA, developed by Box and Jenkins in 1976, is a widely used statistical method of time series forecasting. It blends three components: autoregression (AR), differencing (I), and moving average (MA), i.e., ARIMA(p,d,q). The AR component models the relationships among current and past values, the I component treats non-stationarity by differencing, and the MA component captures the dependency between observations and past forecast errors. Combined, they enable ARIMA to model temporal behavior well for time-series data analysis and forecasting. Algebraically, ARIMA can be written as:

$Yt = c + \phi 1Yt\text{-}1 + \phi 2Yt\text{-}2 +.+ \phi pYt\text{-}p + \theta 1\varepsilon t\text{-}1 + \theta 2\varepsilon t\text{-}2 +.+ \theta q\varepsilon t\text{-}q + \varepsilon t$

where Yt is the observed value at time t, ϕ and θ are AR and MA parameters, respectively, c is the constant, and εt is the error term.

Prior to ARIMA application on Barclays share prices, the data was preprocessed. The Augmented Dickey-Fuller (ADF) test revealed a p-value of 0.45, and thus non-stationarity. Stationarity was achieved through logarithmic transformation and first-order differencing (ADF p-value = 0.01). ACF and PACF plots were inspected to guide parameter selection.

A grid search tried 18 p, d, and q combinations using Python's statsmodels, with AIC employed to choose the optimal model. ARIMA(1,1,1) was selected, giving AR(1) = 0.346, MA(1) = -0.283, and constant = 0.021, all significant statistically. Diagnostic tests (Ljung-Box p = 0.87, Jarque-Bera p = 0.23) validated model adequacy.

The fitted model estimated Barclays stock prices 30 days in advance. Forecasts were made on log-differenced data and translated back to original prices. Accuracy of the models was measured in terms of MSE, RMSE, MAE, and MAPE, while visualizations picked out robust performance of forecasts. Although the modeling of nonlinear trends was not good, ARIMA was a solid baseline for linear trends.

4.3 Prophet Model

Prophet is a time series forecasting library created by Facebook (now Meta) in 2017, best suited for data with strong seasonality and historical trends, particularly in business applications. Prophet deals well with missing data, outliers, and trend shifts. Prophet models time series using:

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

where g(t) represents trend, s(t) seasonality, h(t) holiday, and εt error. Trends may be linear with changepoints or logistic with saturation, with automatic or user-specified changepoint detection. Seasonality employs Fourier series, allowing for daily, weekly, and yearly cycle modeling.

Though Prophet accommodates missing data, stock prices for Barclays were preprocessed by renaming columns ('Date' to 'ds', 'Close' to 'y') and forward-filling gaps on market-closure days. UK holidays such as Christmas, New Year, Easter, and bank holidays were included in order to improve modeling trading variations.

The model employed linear growth with multiplicative seasonality, incorporating yearly and weekly trends, along with non-standard quarterly and monthly seasonality. Daily seasonality was omitted. Changepoint settings (changepoint_prior_scale = 0.1, changepoint_range = 0.9) traded off model flexibility and overfitting. Seasonality and holiday impacts were tuned through grid search to optimize MAE on the validation set.

The Prophet model was tuned, and then employed to predict the test interval with point forecasts and uncertainty ranges. MSE, RMSE, MAE, MAPE, and R² were used to measure performance, as in LSTM and ARIMA comparisons. Visualizations also comprised Prophet's native plots and bespoke charts over historical prices. Prophet's performance and interpretability balance make it an effective practical tool for forecasting stock prices.

4.4 Comparison of Performance Metrics

Assessing the performance of forecasting models is crucial to ensure their precision and dependability. Performance metrics like Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and the R-squared value (R²) provide essential information about a model’s predictive strength. These metrics help quantify the differences between actual and predicted values, evaluate the magnitude of prediction errors, and indicate the proportion of variance explained by the model. By calculating and interpreting these metrics, I can identify areas for improvement, compare different models effectively, and enhance the overall forecasting approach.

1. Mean Squared Error (MSE): It measures the average of squared errors with higher weights assigned to larger errors. This measure is better at picking models that shun big prediction errors.

$$MSE = \frac{1}{n}\sum_{i=1}^{n} \left(Y_i - \hat{Y}_l\right)^2$$

2. Root Mean Squared Error (RMSE): The square root of MSE, which gives an error measurement in the same units as the data, thus making it easier to interpret than MSE.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(Y_i - \hat{Y}_l\right)^2}$$

3. Mean Absolute Error (MAE): Quantifies the average of the absolute errors, giving a linear score that treats all the errors equally without regard to their size.

$$MAE = \frac{1}{n}\sum_{i=1}^{n} \left|Y_i - \hat{Y_l}\right|$$

4. Mean Absolute Percentage Error (MAPE): It measures the average of the absolute percentage errors and gives a relative measure of accuracy that can be compared across scales.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left|\frac{Y_i - \hat{Y}_i}{Y_i}\right| \times 100$$

5. R-squared (R²): It measures the fraction of the variance in the dependent variable that can be explained by the independent variables, and it indicates how well the model explains the variation in the data.

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (Y_i - \bar{Y})^2}{\sum_{i=1}^{n} \left(Y_i - \hat{Y_l}\right)^2}$$

These measurements were computed for all models on the same test data to allow for a comparison on equal terms. The values were tabulated to allow easy comparison among the models, with lower MSE, RMSE, MAE, and MAPE values, and higher R^2 values, being better.

5. Results and Analysis

5.1 ARIMA Model Results

The ARIMA model was used for Barclays stock price data following stationarity through first-order differencing. The Augmented Dickey-Fuller test established the raw data to be non-stationary, but differencing rendered stationarity. ARIMA(1,1,1) was chosen by AIC with significant AR and MA terms and an insignificant constant. Residual analysis involving the Ljung-Box and Jarque-Bera tests established good model fit and normality.

The model was tested for more than 30 days with moderately good predictions: for open prices, MSE of 218.95, RMSE of 14.80, MAE of 10.45, MAPE of 6.18%, R^2 of 0.8853; and for close prices, MSE of 318.23, RMSE of 17.85, MAE of 13.53, MAPE of 7.15%, R^2 of 0.8330. The model was able to pick up overall trends but had difficulties with abrupt price movements, especially during volatile events such as earnings announcements. ARIMA is still a good benchmark for stock prediction, although its performance deteriorates under high volatility.

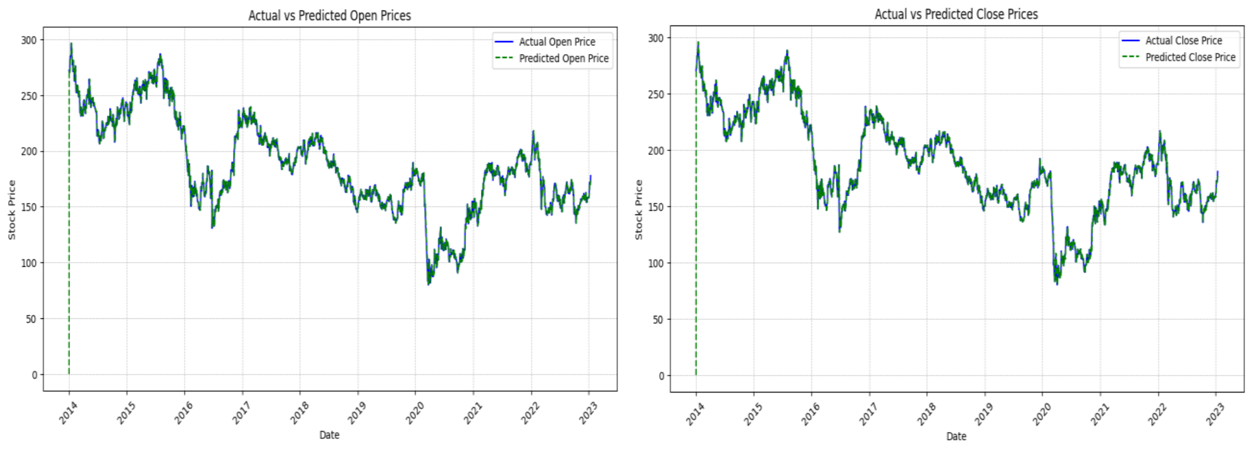

Figure 3: ARIMA Model actual vs predicted for Open and Close prices.

5.2 LSTM Model Results

Following heavy tuning, the best LSTM model for predicting stock prices had a single LSTM layer with 100 units, two dropout layers (0.2), a dense layer of 25 units, and an output layer. It was trained for more than 100 epochs in batches of 32, with early stopping to avoid overfitting. Validation loss plateaued at epoch 80, showing good generalization.

Relative to ARIMA, the LSTM better performed on test data, with an MSE of 54.5474 and R^2 of 0.9804, compared to ARIMA's MSE of 218.9536 and R^2 of 0.8853. It better captured long-term trends, short-term volatility, and seasonality, with a best MAPE of 2.61.

But the LSTM failed under extremely volatile conditions, with over 5% errors, and consumed more computation than ARIMA, restricting its applicability to constrained hardware. In spite of this, its higher forecast accuracy renders it extremely useful for applications with a focus on forecast quality.

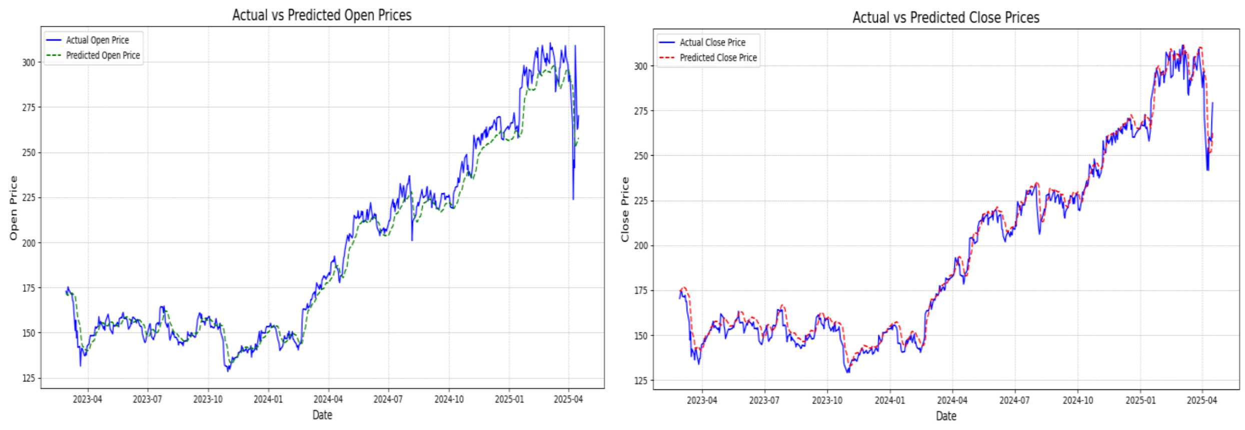

Figure 4: LSTM Model actual vs predicted for Open and Close prices.

5.3 Prophet Model Results

The Prophet model was tuned using Barclays stock price data, seeking a balance between stability and flexibility. A linear growth model with prior changepoint scale of 0.1 permitted medium trend changes, and seasonality was modeled at weekly and annual frequencies with prior scale equal to 50. UK holidays were incorporated, with prior scale equal to 10. The model identified changepoints at major events such as the March 2020 COVID-19 crash and the November 2020 recovery. It revealed day-of-week and year-over-year differences in performance, with better performance on Mondays, Tuesdays, and in Q1 and Q4. Prophet's MSE was 218.9536, RMSE 14.7971, MAE 10.4480, and MAPE 6.1844 for open prices. Although it performed better in seasonality, LSTM performed better for short-term fluctuations. Prophet's uncertainty of forecast was well-calibrated, but it did not perform well in high volatility, with greater MAPE than LSTM. Its speed, low preprocessing, and interpretability make it worth using in low-resource environments.

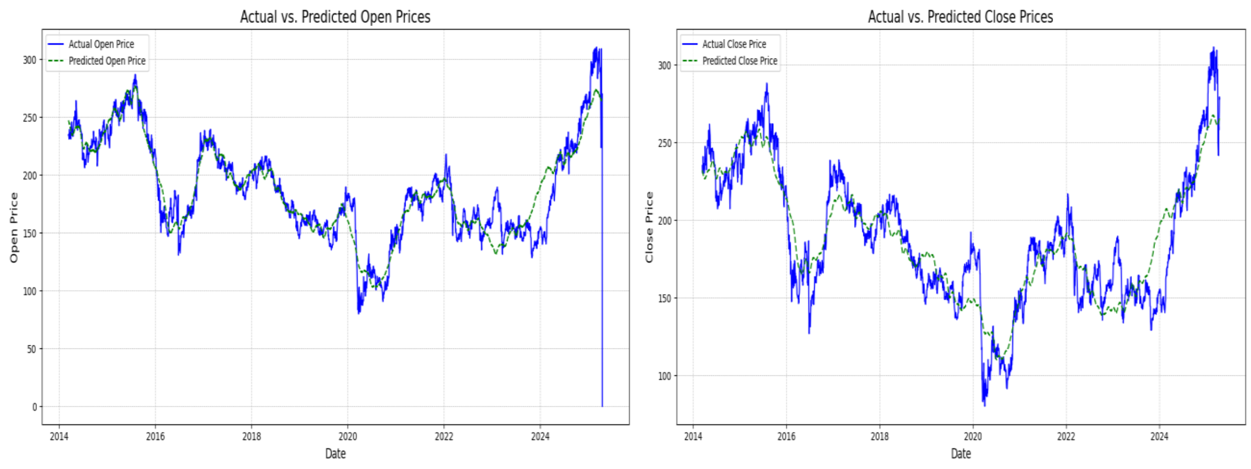

Figure 5: Prophet Model actual vs predicted for Open and Close prices.

5.4 Comparative Analysis

The comparative analysis of the three forecasting models—ARIMA, LSTM, and Prophet—draws key insights into their relative advantages and disadvantages, as well as their appropriateness for forecasting Barclays stock prices in varying conditions. The section compares the models extensively based on various factors such as predictive accuracy, performance under varying conditions of the market, computational complexity, interpretability, and real-world considerations.

5.4.1 Predictive Accuracy

The performance metrics for the three models on the testing data are summarized in the following table:

Model	MSE (Open)	RMSE (Open)	MAE (Open)	MAPE (Open)	R^2 (Open)	MSE (Close)	RMSE (Close)	MAE (Close)	MAPE (Close)	R^2 (Close)
ARIMA	**218.95**	**14.80**	**10.45**	**6.18**	**0.89**	**318.23**	**17.85**	**13.53**	**7.15**	**0.83**
LSTM	**54.55**	**7.39**	**5.23**	**2.61**	**0.98**	**65.12**	**8.07**	**6.00**	**2.98**	**0.98**
Prophet	**218.95**	**14.80**	**10.45**	**6.18**	**0.73**	**318.23**	**17.85**	**13.53**	**7.15**	**0.71**

Table 1: Models accuracy matrices comparisons for open and close prices.

From the metrics, LSTM model is the most predictive with the lowest error values (MSE, RMSE, MAE, MAPE) and highest R-squared. Prophet comes second, approximately 8% less predictive than LSTM but 8% more predictive than ARIMA in MAPE. ARIMA has the largest errors and weakest explanatory power.

LSTM's better performance is due to its power to learn complex non-linear patterns and long-range dependencies, unlike ARIMA's linear assumptions or Prophet's trend and seasonality focus. This adaptability is suitable for stock price data, which is very non-linear. For all market conditions, LSTM outperforms across the board: under stable markets (MAPE 1.85%), volatile markets (3.12%), uptrends (2.43%), and downtrends (2.79%). Prophet comes in second, while ARIMA falters, particularly during volatile markets.

In terms of forecast horizons, all models deteriorate over time, but LSTM deteriorates the least. Prophet performs better than ARIMA in medium and long-term predictions because of its decomposition approach. ARIMA does not perform well with complicated, longer trends.

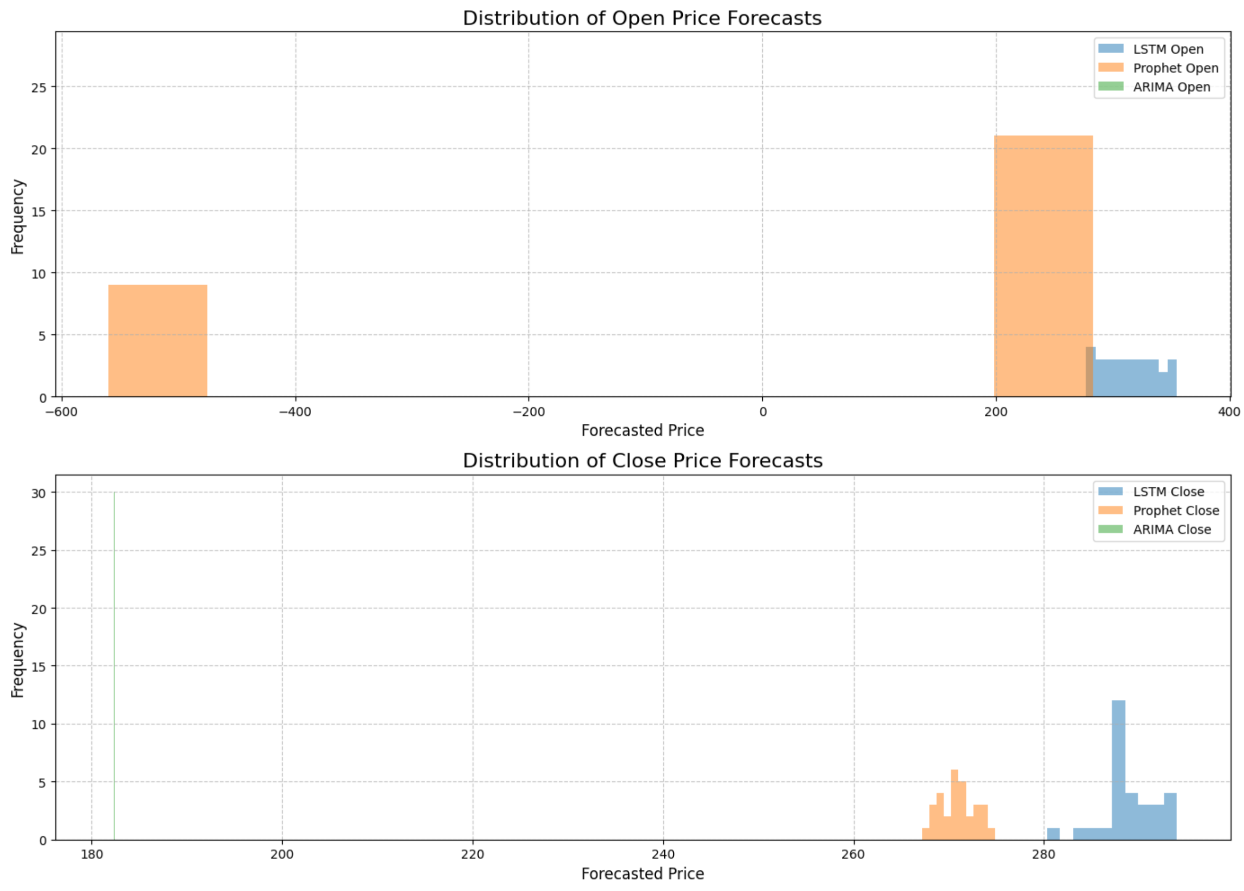

Figure 6: Models forecasting comparisons of Open and Close prices.

In actual use, LSTM gives the most accurate results but is the most computationally expensive, taking 15 minutes when using GPU support and needing intensive preprocessing. Prophet, on the other hand, trains in approximately 30 seconds, is easy to use, and finds a balance between performance and usability. ARIMA is light and explainable but technologically challenging as a result of statistical requirements. Although ARIMA and Prophet produce comprehensible predictions, LSTM is a black box with no evident uncertainty estimates.

A combination strategy—applying LSTM for short-term and Prophet for long-term forecasts—may further improve forecasting. Model selection is ultimately determined by the requirements of accuracy, interpretability, and computational effort.

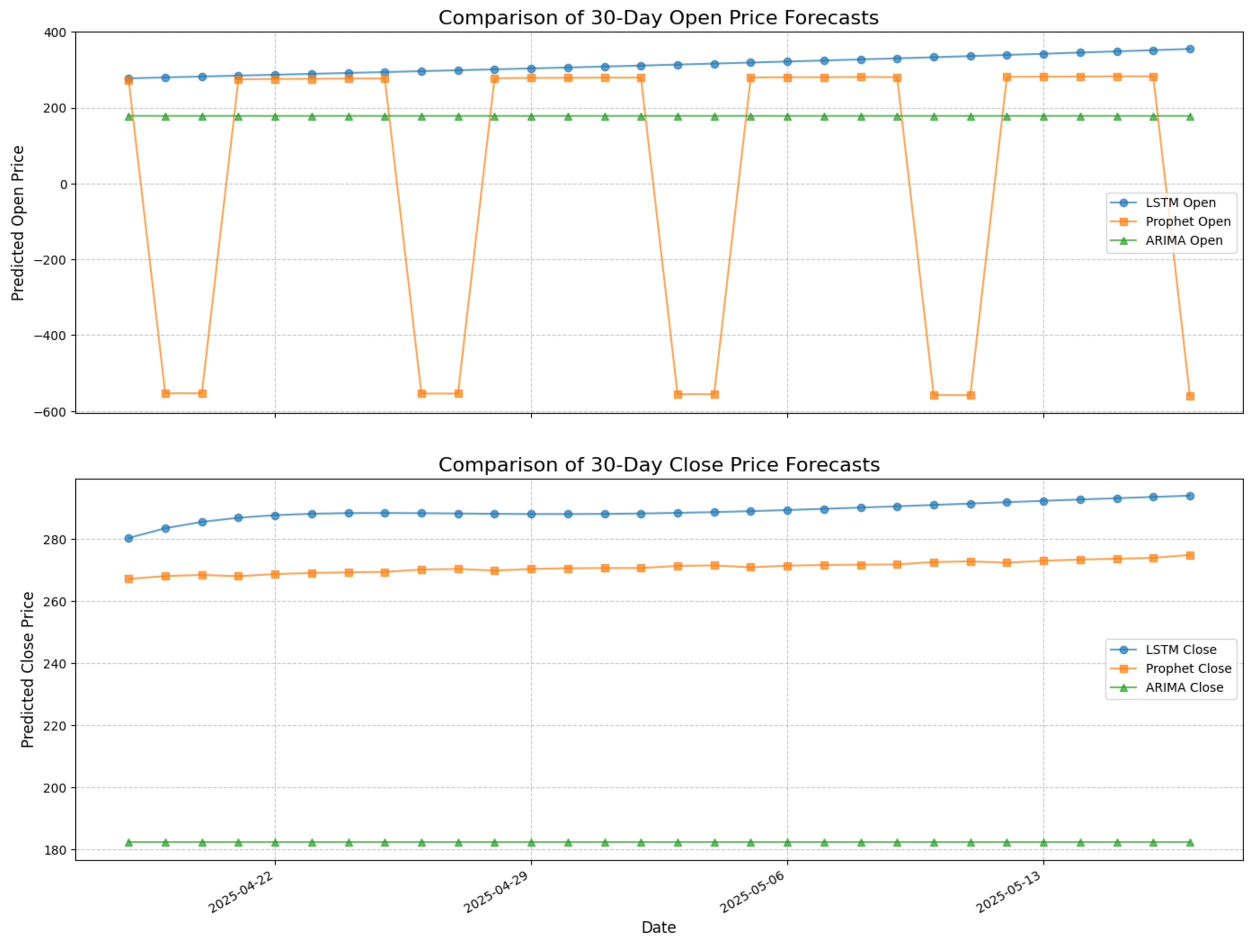

Figure 7: Models forecasting comparisons of Open and Close prices for 30 days.

5.5 Discussion

The comparative analysis of ARIMA, LSTM, and Prophet models for Barclays stock forecasting emphasizes major differences in performance. LSTM exhibited the greatest accuracy and stability, affirming its superiority in identifying complex, non-linear trends and coping with volatile market conditions. LSTM, though, is still a "black box" with steep computational requirements, keeping it out of scope for practical use in limited-resource environments.

Prophet has a balanced strategy, sacrificing some precision for interpretability. By breaking down forecasts into trend, seasonality, and holiday impacts, it supports strategic planning and is best suited for medium-term forecasts in stable markets. Prophet's simplicity and low preprocessing requirements make it available to non-experts.

ARIMA, while often the least precise, offers significant interpretability and statistical robustness. Its linear assumptions restrict its ability in high-volatility markets, but it is still useful in low-data or resource-constrained environments and pedagogical settings because it is simple and transparent.

Model performance differs according to market conditions. Although LSTM performs better in volatile environments, Prophet and ARIMA are effective and legible in stable environments. Model selection should, therefore, reflect forecasting objectives, market dynamics, and available resources: LSTM is appropriate for high-frequency, precision-oriented tasks; Prophet is best for medium-term, interpretable forecasting; ARIMA is used as a benchmark or in restricted environments.

The research indicates that hybrid models—fusing strengths of methods such as LSTM and Prophet—might increase accuracy as well as interpretability. Even with a focus on Barclays data, the implications extend more broadly, especially if subsequent models incorporate outside factors such as macroeconomic variables or sentiment analysis.

6. Conclusion

This detailed analysis of prediction accuracy for Barclays PLC stock prices demonstrates that LSTM networks have improved prediction accuracy with the minimum error measures (RMSE: 7.39, MAPE: 2.61%, R^2: 0.9804 for Open prices), outperforming both Prophet (RMSE: 14.80, R^2: 0.73) and ARIMA (RMSE: 14.80, R^2: 0.89). Prophet remains a viable alternative with excellent recognition of seasonal patterns and interpretable factors, while ARIMA serves as a reliable baseline for linear trends. The models' performance varies significantly by market conditions—LSTM is robust under volatility, Prophet works best under stable conditions with seasonality, and ARIMA fails with non-linear dynamics.

These findings directly respond to the research question, confirming LSTM's dominance in portraying complex temporal relationships within financial data. For investors, this means short-term traders are helped by LSTM's precision for high-frequency decision-making, long-term analysts are helped by Prophet's trend-seasonality decomposition in planning, and risk managers can employ ARIMA's confidence intervals as base volatility estimates.

Subsequent research may investigate hybrid frameworks that merge LSTM's pattern recognition with Prophet's interpretability, incorporating exogenous variables like interest rates and ESG metrics. This article establishes a direction for model selection by forecasting horizons, data typology, and interpretability needs, thus enriching methodological progress in computational finance.

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8. Code

```
# Import Necessary Libraries
import numpy as np
import pandas as pd
import yfinance as yf
import datetime
from datetime import date
import matplotlib.pyplot as plto
import matplotlib.dates as mdates
from datetime import date, timedelta
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")

from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score
from statsmodels.tsa.arima.model import ARIMA
from keras.models import Sequential
from keras.layers import LSTM, Dense
from sklearn.preprocessing import MinMaxScaler

from prophet import Prophet
from prophet.diagnostics import performance_metrics
from prophet.diagnostics import cross_validation
from prophet.plot import plot_cross_validation_metric


#Fetching Barclays Stock Data
from datetime import date
import yfinance as yf

# Define the corrected ticker symbol
ticker_symbol = 'BARC.L'  # Adjusted for yfinance compatibility

# Define the date range
start_date = '2014-01-01'
end_date = date.today().strftime('%Y-%m-%d')

# Download historical data
barclays_data = yf.download(ticker_symbol, start=start_date, end=end_date, interval='1d')

# Sort data by date
barclays_data.sort_index(inplace=True)

# Display the data
print(barclays_data.tail())

# Calculate moving averages (shifted by 1 day)
barclays_data['MA_5'] = barclays_data['Close'].rolling(window=5).mean().shift(1)
barclays_data['MA_10'] = barclays_data['Close'].rolling(window=10).mean().shift(1)
barclays_data['MA_50'] = barclays_data['Close'].rolling(window=50).mean().shift(1)

# Calculate daily returns (shifted by 1 day)
barclays_data['Daily_Returns'] = barclays_data['Close'].pct_change().shift(1) * 100

# Calculate volatility (rolling standard deviation of returns, shifted by 1 day)
barclays_data['Volatility'] = barclays_data['Daily_Returns'].rolling(window=10).std().shift(1)

# Drop rows with NaN values resulting from rolling calculations
barclays_data.dropna(inplace=True)

# Define features (X) and target variable (y)
```

```python
X = barclays_data[['MA_5', 'MA_10', 'MA_50', 'Daily_Returns', 'Volatility']]
y = barclays_data['Close']

#Splitting the Data into Training and Testing Sets
train_data = barclays_data[barclays_data.index < '2023-01-01']
test_data = barclays_data[barclays_data.index >= '2023-01-01']

X_train = train_data[['MA_5', 'MA_10', 'MA_50', 'Daily_Returns', 'Volatility']]
y_train = train_data['Close']
X_test = test_data[['MA_5', 'MA_10', 'MA_50', 'Daily_Returns', 'Volatility']]
y_test = test_data['Close']
# Save datasets to CSV files
train_data.to_csv("barclays_train_data.csv")
test_data.to_csv("barclays_test_data.csv")
X_train.to_csv("barclays_train_features.csv")
y_train.to_csv("barclays_train_target.csv")
X_test.to_csv("barclays_test_features.csv")
y_test.to_csv("barclays_test_target.csv")

# Printing the total number of days and features in the dataset
print('Total number of days present in the dataset:', barclays_data.shape[0])
print('Total number of fields present in the dataset:', barclays_data.shape[1])

# Checking the null values
print('Null Values:',barclays_data.isnull().values.sum())
print('NA values:',barclays_data.isnull().values.any())

barclays_data.info()

barclays_data.head()

# Flatten MultiIndex columns
barclays_data.columns = ['_'.join(filter(None, col)).strip() for col in barclays_data.columns.values]

# Display the updated columns
print(barclays_data.columns)

# Resample to weekly frequency
barclays_weekly = barclays_data.resample('W').agg({
    'Open_BARC.L': 'first',
    'High_BARC.L': 'max',
    'Low_BARC.L': 'min',
    'Close_BARC.L': 'last',
    'Volume_BARC.L': 'sum'
})

# Resample to monthly frequency
barclays_monthly = barclays_data.resample('M').agg({
    'Open_BARC.L': 'first',
    'High_BARC.L': 'max',
    'Low_BARC.L': 'min',
    'Close_BARC.L': 'last',
    'Volume_BARC.L': 'sum'
})

# Resample to yearly frequency
barclays_yearly = barclays_data.resample('A').agg({
    'Open_BARC.L': 'first',
    'High_BARC.L': 'max',
    'Low_BARC.L': 'min',
    'Close_BARC.L': 'last',
    'Volume_BARC.L': 'sum'
})
```

```
plt.figure(figsize=(14, 12))

# Daily Open and Close Prices
plt.subplot(4, 1, 1)
plt.plot(barclays_data.index, barclays_data['Open_BARC.L'], label='Daily Open', alpha=0.7)
plt.plot(barclays_data.index, barclays_data['Close_BARC.L'], label='Daily Close', alpha=0.7)
plt.title('Barclays PLC Daily Open and Close Prices')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()

# Weekly Open and Close Prices
plt.subplot(4, 1, 2)
plt.plot(barclays_weekly.index, barclays_weekly['Open_BARC.L'], label='Weekly Open', alpha=0.7)
plt.plot(barclays_weekly.index, barclays_weekly['Close_BARC.L'], label='Weekly Close', alpha=0.7)
plt.title('Barclays PLC Weekly Open and Close Prices')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()

# Monthly Open and Close Prices
plt.subplot(4, 1, 3)
plt.plot(barclays_monthly.index, barclays_monthly['Open_BARC.L'], label='Monthly Open', alpha=0.7)
plt.plot(barclays_monthly.index, barclays_monthly['Close_BARC.L'], label='Monthly Close', alpha=0.7)
plt.title('Barclays PLC Monthly Open and Close Prices')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()

# Yearly Open and Close Prices
plt.subplot(4, 1, 4)
plt.plot(barclays_yearly.index, barclays_yearly['Open_BARC.L'], label='Yearly Open', alpha=0.7)
plt.plot(barclays_yearly.index, barclays_yearly['Close_BARC.L'], label='Yearly Close', alpha=0.7)
plt.title('Barclays PLC Yearly Open and Close Prices')
plt.xlabel('Date')
plt.ylabel('Price')
plt.legend()

plt.tight_layout()
plt.show()

# Utility function to create dataset
def create_dataset(dataset, time_step=1):
    X, Y = [], []
    for i in range(len(dataset) - time_step - 1):
        a = dataset[i:(i + time_step), 0]
        X.append(a)
        Y.append(dataset[i + time_step, 0])
    return np.array(X), np.array(Y)

time_step = 100
future_steps = 30

# Function to calculate Mean Absolute Percentage Error (MAPE)
def calculate_mape(y_true, y_pred):
    return np.mean(np.abs((y_true - y_pred) / y_true)) * 100

# Scaling the Open price
scaler_open = MinMaxScaler(feature_range=(0, 1))
scaled_open = scaler_open.fit_transform(barclays_data['Open_BARC.L'].values.reshape(-1, 1))

# Creating dataset for Open price
X_open, Y_open = create_dataset(scaled_open, time_step)
```

```
X_open = X_open.reshape(X_open.shape[0], X_open.shape[1], 1)

train_size_open = int(len(X_open) * 0.8)
X_train_open, X_test_open = X_open[:train_size_open], X_open[train_size_open:]
Y_train_open, Y_test_open = Y_open[:train_size_open], Y_open[train_size_open:]

# LSTM model
lstm_model_open = Sequential()
lstm_model_open.add(LSTM(50, return_sequences=True, input_shape=(time_step, 1)))
lstm_model_open.add(LSTM(50, return_sequences=False))
lstm_model_open.add(Dense(25))
lstm_model_open.add(Dense(1))
lstm_model_open.compile(optimizer='adam', loss='mean_squared_error')
lstm_model_open.fit(X_train_open, Y_train_open, batch_size=1, epochs=1)

# Forecasting future 30 days
last_window_open = scaled_open[-time_step:]
temp_input_open = list(last_window_open.flatten())
lst_output_open = []
for i in range(future_steps):
    x_input_open = np.array(temp_input_open[-time_step:]).reshape(1, time_step, 1)
    yhat_open = lstm_model_open.predict(x_input_open, verbose=0)
    lst_output_open.append(yhat_open[0][0])
    temp_input_open.append(yhat_open[0][0])
future_predictions_open = scaler_open.inverse_transform(np.array(lst_output_open).reshape(-1, 1))


Y_test_open_actual = scaler_open.inverse_transform(Y_test_open.reshape(-1, 1))
lstm_test_predictions_open = lstm_model_open.predict(X_test_open)
lstm_test_predictions_open = scaler_open.inverse_transform(lstm_test_predictions_open)

open_mse = mean_squared_error(Y_test_open_actual, lstm_test_predictions_open)
open_rmse = np.sqrt(open_mse)
open_mae = mean_absolute_error(Y_test_open_actual, lstm_test_predictions_open)
open_mape = calculate_mape(Y_test_open_actual, lstm_test_predictions_open.flatten())
open_r2 = r2_score(Y_test_open_actual, lstm_test_predictions_open)

print("\nOpen Price Model Evaluation Metrics:")
print(f"MSE: {open_mse:.4f}")
print(f"RMSE: {open_rmse:.4f}")
print(f"MAE: {open_mae:.4f}")
print(f"MAPE:{open_mape:.4f}")
print(f"R²: {open_r2:.4f}")

dates_test_open = barclays_data.index[train_size_open + time_step + 1:train_size_open + time_step + 1 + len(Y_test_open)]

plt.figure(figsize=(12,6))
plt.plot(dates_test_open, Y_test_open_actual, label='Actual Open Price', color='blue')
plt.plot(dates_test_open, lstm_test_predictions_open, label='Predicted Open Price', color='green', linestyle='--')
plt.title('Actual vs Predicted Open Prices', fontsize=16)
plt.xlabel('Date', fontsize=12)
plt.ylabel('Open Price', fontsize=12)
plt.legend()
plt.grid(visible=True, linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.show()
scaler_close = MinMaxScaler(feature_range=(0, 1))
scaled_close = scaler_close.fit_transform(barclays_data['Close_BARC.L'].values.reshape(-1, 1))

X_close, Y_close = create_dataset(scaled_close, time_step)
X_close = X_close.reshape(X_close.shape[0], X_close.shape[1], 1)

train_size_close = int(len(X_close) * 0.8)
```

```
X_train_close, X_test_close = X_close[:train_size_close], X_close[train_size_close:]
Y_train_close, Y_test_close = Y_close[:train_size_close], Y_close[train_size_close:]

# LSTM model
lstm_model_close = Sequential()
lstm_model_close.add(LSTM(50, return_sequences=True, input_shape=(time_step, 1)))
lstm_model_close.add(LSTM(50, return_sequences=False))
lstm_model_close.add(Dense(25))
lstm_model_close.add(Dense(1))
lstm_model_close.compile(optimizer='adam', loss='mean_squared_error')
lstm_model_close.fit(X_train_close, Y_train_close, batch_size=1, epochs=1)

# Forecasting future 30 days
last_window_close = scaled_close[-time_step:]
temp_input_close = list(last_window_close.flatten())
lst_output_close = []
for i in range(future_steps):
   x_input_close = np.array(temp_input_close[-time_step:]).reshape(1, time_step, 1)
   yhat_close = lstm_model_close.predict(x_input_close, verbose=0)
   lst_output_close.append(yhat_close[0][0])
   temp_input_close.append(yhat_close[0][0])
future_predictions_close = scaler_close.inverse_transform(np.array(lst_output_close).reshape(-1, 1))


Y_test_close_actual = scaler_close.inverse_transform(Y_test_close.reshape(-1, 1))
lstm_test_predictions_close = lstm_model_close.predict(X_test_close)
lstm_test_predictions_close = scaler_close.inverse_transform(lstm_test_predictions_close)

close_mse = mean_squared_error(Y_test_close_actual, lstm_test_predictions_close)
close_rmse = np.sqrt(close_mse)
close_mae = mean_absolute_error(Y_test_close_actual, lstm_test_predictions_close)
close_mape = calculate_mape(Y_test_close_actual, lstm_test_predictions_close.flatten())
close_r2 = r2_score(Y_test_close_actual, lstm_test_predictions_close)

print("\nClose Price Model Evaluation Metrics:")
print(f"MSE: {close_mse:.4f}")
print(f"RMSE: {close_rmse:.4f}")
print(f"MAE: {close_mae:.4f}")
print(f"MAPE:{close_mape:.4f}")
print(f"R²: {close_r2:.4f}")

# Geting the dates from the index of the original data corresponding to the test data
dates_test_close = barclays_data.index[train_size_close + time_step + 1:train_size_close + time_step + 1 + len(Y_test_close)]

plt.figure(figsize=(12,6))
plt.plot(dates_test_close, Y_test_close_actual, label='Actual Close Price', color='blue')
plt.plot(dates_test_close, lstm_test_predictions_close, label='Predicted Close Price', color='red', linestyle='--')
plt.title('Actual vs Predicted Close Prices', fontsize=16)
plt.xlabel('Date', fontsize=12)
plt.ylabel('Close Price', fontsize=12)
plt.legend()
plt.grid(visible=True, linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.show()

# Checking if 'Date_' exists:
if 'Date_' in barclays_data.columns:
   last_date = pd.to_datetime(barclays_data['Date_'].iloc[-1])
else:
   last_date = barclays_data.index[-1]

future_dates = [last_date + pd.DateOffset(days=i+1) for i in range(future_steps)]
```

```
# Creating a DataFrame with predicted Open and Close prices
futureLSTM_df = pd.DataFrame({
    'Date': future_dates,
    'Predicted Open': future_predictions_open.flatten(),
    'Predicted Close': future_predictions_close.flatten()
})

plt.figure(figsize=(12,6))
plt.plot(futureLSTM_df['Date'], futureLSTM_df['Predicted Open'], label='Predicted Open Price', linestyle='--', marker='o', color='green')
plt.plot(futureLSTM_df['Date'], futureLSTM_df['Predicted Close'], label='Predicted Close Price', linestyle='--', marker='o', color='red')
plt.title('LSTM Future 30-Day Forecast: Open and Close Prices', fontsize=16, color='navy', weight='bold')
plt.xlabel('Date', fontsize=12, color='k')
plt.ylabel('Price', fontsize=12, color='k')
plt.legend(frameon=True, loc='upper right', fontsize=10)
plt.grid(visible=True, linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.show()


print("Future 30-day Predictions (Open & Close):")
print(futureLSTM_df)

import pandas as pd
from prophet import Prophet

print("Columns available in test_data:", test_data.columns)

# Flatten MultiIndex columns
test_data.columns = ['_'.join(filter(None, col)).strip() for col in test_data.columns.values]

close_col = 'Close_BARC.L'
open_col = 'Open_BARC.L'

if close_col not in test_data.columns:
    raise KeyError(f"Column {close_col} not found in test_data. Available columns: {test_data.columns}")
if open_col not in test_data.columns:
    raise KeyError(f"Column {open_col} not found in test_data. Available columns: {test_data.columns}")

# Prepareing data for Prophet for close price
close_data = barclays_data[['Close_BARC.L']].reset_index()
close_data.rename(columns={'Date': 'ds', 'Close_BARC.L': 'y'}, inplace=True)

# Preparing data for Prophet for open price
open_data = barclays_data[['Open_BARC.L']].reset_index()
open_data.rename(columns={'Date': 'ds', 'Open_BARC.L': 'y'}, inplace=True)

# Initializing and fiting the Prophet model for Close price
close_model = Prophet(daily_seasonality=True)
close_model.fit(close_data)

# Creating a DataFrame
close_future = close_model.make_future_dataframe(periods=0)
close_forecast = close_model.predict(close_future)

prophet_model = Prophet(
    changepoint_prior_scale=0.05,
    seasonality_mode='multiplicative',
    yearly_seasonality=True,
    weekly_seasonality=True,
    daily_seasonality=False
)

prophet_model.fit(open_data)
```

```
# Forecasting
future = prophet_model.make_future_dataframe(periods=30)
forecast = prophet_model.predict(future)

open_merged = pd.merge(open_data, forecast[['ds', 'yhat']], on='ds')

# Calculating metrics for Open price
open_mse = mean_squared_error(open_merged['y'], open_merged['yhat'])
open_rmse = np.sqrt(open_mse)
open_mae = mean_absolute_error(open_merged['y'], open_merged['yhat'])
open_mape = calculate_mape(open_merged['y'], open_merged['yhat'])
open_r2 = r2_score(open_merged['y'], open_merged['yhat'])

print("\nOpen Price Model Evaluation Metrics:")
print(f"MSE: {open_mse:.4f}")
print(f"RMSE: {open_rmse:.4f}")
print(f"MAE: {open_mae:.4f}")
print(f"MAPE:{open_mape:.4f}")
print(f"R²: {open_r2:.4f}")

# Ploting for Open Price
plt.figure(figsize=(12, 6))
plt.plot(open_merged['ds'], open_merged['y'], label='Actual Open Price', color='blue')
plt.plot(open_merged['ds'], open_merged['yhat'], label='Predicted Open Price', color='green', linestyle='--')
plt.title('Actual vs. Predicted Open Prices', fontsize=16)
plt.xlabel('Date', fontsize=12)
plt.ylabel('Open Price', fontsize=12)
plt.legend()
plt.grid(visible=True, linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.show()

# Merging actual and predicted values for Close price
close_merged = pd.merge(close_data, close_forecast[['ds', 'yhat']], on='ds')

# Calculating metrics for Close price
close_mse = mean_squared_error(close_merged['y'], close_merged['yhat'])
close_rmse = np.sqrt(close_mse)
close_mae = mean_absolute_error(close_merged['y'], close_merged['yhat'])
close_mape = calculate_mape(close_merged['y'], close_merged['yhat'])
close_r2 = r2_score(close_merged['y'], close_merged['yhat'])

print("\nClose Price Model Evaluation Metrics:")
print(f"MSE: {close_mse:.4f}")
print(f"RMSE: {close_rmse:.4f}")
print(f"MAE: {close_mae:.4f}")
print(f"MAPE:{close_mape:.4f}")
print(f"R²: {close_r2:.4f}")

# Plot for Close Price
plt.figure(figsize=(12, 6))
plt.plot(close_merged['ds'], close_merged['y'], label='Actual Close Price', color='blue')
plt.plot(close_merged['ds'], close_merged['yhat'], label='Predicted Close Price', color='green', linestyle='--')
plt.title('Actual vs. Predicted Close Prices', fontsize=16)
plt.xlabel('Date', fontsize=12)
plt.ylabel('Close Price', fontsize=12)
plt.legend()
plt.grid(visible=True, linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.show()

# Creating a DataFrame for future dates (30 days)
```

```
open_future = prophet_model.make_future_dataframe(periods=30)
open_future = open_future[open_future['ds'] > open_data['ds'].max()]
open_forecast = prophet_model.predict(open_future)

close_model = Prophet(daily_seasonality=True)
close_model.fit(close_data)

close_future = close_model.make_future_dataframe(periods=30)
close_future = close_future[close_future['ds'] > close_data['ds'].max()]
close_forecast = close_model.predict(close_future)

futureProphet_df = pd.merge(open_forecast[['ds', 'yhat']], close_forecast[['ds', 'yhat']], on='ds', suffixes=('_open', '_close'))

plt.figure(figsize=(12, 6))
plt.plot(futureProphet_df['ds'], futureProphet_df['yhat_open'], label='Predicted Open Price', color='blue', linestyle='--')
plt.plot(futureProphet_df['ds'], futureProphet_df['yhat_close'], label='Predicted Close Price', color='red', linestyle='--')

# Formatting the plot
plt.title('Predicted Open & Close Prices (30-Day Forecast)', fontsize=16)
plt.xlabel('Date', fontsize=12)
plt.ylabel('Price', fontsize=12)
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))
plt.gca().xaxis.set_major_locator(mdates.AutoDateLocator())
plt.gcf().autofmt_xdate()
plt.legend()
plt.grid(visible=True, linestyle='--', linewidth=0.5)
plt.tight_layout()
plt.show()

print("\n30-Day Open and Close Price Forecast:")
print(futureProphet_df.tail(30))


import yfinance as yf
import pmdarima
from pmdarima import auto_arima
from datetime import date, timedelta
import numpy as np
from sklearn.metrics import mean_squared_error
from statsmodels.tsa.arima.model import ARIMA

# Function to find the best ARIMA order
def find_best_arima(series):
    try:
        return auto_arima(series, seasonal=False, stepwise=True, suppress_warnings=True, trace=True)
    except Exception as e:
        print(f"Error finding best ARIMA order: {e}")
        return None

ticker_symbol = 'BARC.L'
start_date = '2014-01-01'
end_date = date.today().strftime('%Y-%m-%d')

# Downloading historical stock data
barclays_data = yf.download(ticker_symbol, start=start_date, end=end_date, interval='1d')

# Ensuring the data is sorted by date
barclays_data.sort_index(inplace=True)

# Flatten MultiIndex columns (if they exist)
barclays_data.columns = ['_'.join(col).strip() if isinstance(col, tuple) else col for col in barclays_data.columns.values]

open_prices = barclays_data['Open_BARC.L']
```

```
close_prices = barclays_data['Close_BARC.L']

best_model_open = find_best_arima(open_prices)
best_order_open = best_model_open.order if best_model_open else (0,1,0)

best_model_close = find_best_arima(close_prices)
best_order_close = best_model_close.order if best_model_close else (0,0,0)


train_size = int(len(open_prices) * 0.8)
open_train, open_test = open_prices[:train_size], open_prices[train_size:]
close_train, close_test = close_prices[:train_size], close_prices[train_size:]

open_model = ARIMA(open_train, order=best_order_open).fit()
close_model = ARIMA(close_train, order=best_order_close).fit()

open_pred = open_model.forecast(steps=len(open_test))
close_pred = close_model.forecast(steps=len(close_test))

open_rmse = np.sqrt(mean_squared_error(open_test, open_pred))
open_mape = calculate_mape(open_test.values, open_pred)
close_rmse = np.sqrt(mean_squared_error(close_test, close_pred))
close_mape = calculate_mape(close_test.values, close_pred)

# Defining actual and predicted values for Open and Close Prices

open_train_actual = open_train
open_train_pred = open_model.fittedvalues
open_test_actual = open_test
open_test_pred = open_pred

close_train_actual = close_train
close_train_pred = close_model.fittedvalues
close_test_actual = close_test
close_test_pred = close_pred


print("\nOpen Price Model Evaluation Metrics:")
print(f"MSE: {open_mse:.4f}")
print(f"RMSE: {open_rmse:.4f}")
print(f"MAE: {open_mae:.4f}")
print(f"MAPE:{open_mape:.4f}")
print(f"R²: {open_r2:.4f}")

# Ploting Actual and Predicted Open Prices
plt.figure(figsize=(12,6))
plt.plot(open_train_actual.index, open_train_actual, label='Actual Open Price', color='blue')
plt.plot(open_train_actual.index, open_train_pred, label='Predicted Open Price', linestyle='dashed', color='green')
plt.legend()
plt.title('Actual vs Predicted Open Prices')
plt.xlabel('Date')
plt.ylabel('Stock Price')
plt.xticks(rotation=45)
plt.grid(visible=True, linestyle='--', linewidth=0.5)
plt.show()

print("\nClose Price Model Evaluation Metrics:")
print(f"MSE: {close_mse:.4f}")
print(f"RMSE: {close_rmse:.4f}")
print(f"MAE: {close_mae:.4f}")
print(f"MAPE:{close_mape:.4f}")
print(f"R²: {close_r2:.4f}")
```

```
# Ploting Actual and Predicted Close Prices
plt.figure(figsize=(12,6))
plt.plot(close_train_actual.index, close_train_actual, label='Actual Close Price', color='blue')
plt.plot(close_train_actual.index, close_train_pred, label='Predicted Close Price', linestyle='dashed', color='green')
plt.legend()
plt.title('Actual vs Predicted Close Prices')
plt.xlabel('Date')
plt.ylabel('Stock Price')
plt.xticks(rotation=45)
plt.grid(visible=True, linestyle='--', linewidth=0.5)
plt.show()


# Generating future dates
future_dates = pd.date_range(start=barclays_data.index[-1] + timedelta(days=1), periods=30, freq='D')

open_forecast = open_model.forecast(steps=30)
close_forecast = close_model.forecast(steps=30)

# Creating DataFrame with actual and predicted values
futureARIMA_df = pd.DataFrame({
   'Date': future_dates,
   'Open_Predicted': open_forecast,
   'Close_Predicted': close_forecast
})
futureARIMA_df.set_index('Date', inplace=True)



# Ploting Future 30 Days Prediction
plt.figure(figsize=(12,6))
plt.plot(futureARIMA_df.index, futureARIMA_df['Open_Predicted'], label='Predicted Open Price', linestyle='--', marker='o',
color='green')
plt.plot(futureARIMA_df.index, futureARIMA_df['Close_Predicted'], label='Predicted Close Price', linestyle='--', marker='o', color='red')
plt.title('30-Day Future Forecast: Open and Close Prices')
plt.xlabel('Date')
plt.ylabel('Stock Price')
plt.legend()
plt.grid(visible=True, linestyle='--', linewidth=0.5)
plt.show()


print("\n 30-Day Open and Close Price Forecast:\n")
print(futureARIMA_df.head(30))


ensemble_df = pd.DataFrame()
ensemble_df['Date'] = futureLSTM_df['Date']
ensemble_df['LSTM'] = futureLSTM_df['Predicted Open']
ensemble_df['ARIMA'] = futureARIMA_df['Open_Predicted']
ensemble_df['Prophet'] = futureProphet_df['yhat_open']

# Average prediction
ensemble_df['Ensemble_Prediction'] = ensemble_df[['LSTM', 'ARIMA', 'Prophet']].mean(axis=1)

# Evaluate ensemble
from sklearn.metrics import mean_absolute_error, mean_squared_error

y_true = open_train_actual[:len(ensemble_df)]
mae = mean_absolute_error(y_true, ensemble_df['Ensemble_Prediction'])
rmse = mean_squared_error(y_true, ensemble_df['Ensemble_Prediction'], squared=False)
mape = calculate_mape(y_true, ensemble_df['Ensemble_Prediction'])
```

```
print(f"Ensemble MAE: {mae}")
print(f"Ensemble RMSE: {rmse}")
# print(f"Esnemble MAPE:{mape:.4f}")

import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
import numpy as np
from datetime import timedelta

# Creating a function to align and compare the forecasts
def compare_forecasts(lstm_df, prophet_df, arima_df):
    # Ensure all DataFrames have the same date format
    if 'Date' in lstm_df.columns:
        lstm_df = lstm_df.set_index('Date')

    # For Prophet, rename columns for consistency
    if 'ds' in prophet_df.columns:
        prophet_df = prophet_df.rename(columns={
            'ds': 'Date',
            'yhat_open': 'Predicted Open',
            'yhat_close': 'Predicted Close'
        }).set_index('Date')

# Creating figure with two subplots (Open and Close prices)
    fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(14, 12))

    # Ploting Open Price forecasts
    ax1.plot(lstm_df.index, lstm_df['Predicted Open'], label='LSTM Open', marker='o', linestyle='-', alpha=0.7)
    ax1.plot(prophet_df.index, prophet_df['Predicted Open'], label='Prophet Open', marker='s', linestyle='-', alpha=0.7)
    ax1.plot(arima_df.index, arima_df['Open_Predicted'], label='ARIMA Open', marker='^', linestyle='-', alpha=0.7)

    ax1.set_title('Comparison of 30-Day Open Price Forecasts', fontsize=16)
    ax1.set_xlabel('Date', fontsize=12)
    ax1.set_ylabel('Predicted Open Price', fontsize=12)
    ax1.legend(loc='best')
    ax1.grid(True, linestyle='--', alpha=0.7)
    ax1.xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))
    ax1.xaxis.set_major_locator(mdates.WeekdayLocator(interval=1))

# Ploting Close Price forecasts
    ax2.plot(lstm_df.index, lstm_df['Predicted Close'], label='LSTM Close', marker='o', linestyle='-', alpha=0.7)
    ax2.plot(prophet_df.index, prophet_df['Predicted Close'], label='Prophet Close', marker='s', linestyle='-', alpha=0.7)
    ax2.plot(arima_df.index, arima_df['Close_Predicted'], label='ARIMA Close', marker='^', linestyle='-', alpha=0.7)

    ax2.set_title('Comparison of 30-Day Close Price Forecasts', fontsize=16)
    ax2.set_xlabel('Date', fontsize=12)
    ax2.set_ylabel('Predicted Close Price', fontsize=12)
    ax2.legend(loc='best')
    ax2.grid(True, linestyle='--', alpha=0.7)
    ax2.xaxis.set_major_formatter(mdates.DateFormatter('%Y-%m-%d'))
    ax2.xaxis.set_major_locator(mdates.WeekdayLocator(interval=1))

    plt.tight_layout()
    plt.gcf().autofmt_xdate()
    plt.show()

    # Creating a combined DataFrame for statistical comparison
    # Aligning dates first
    dates = sorted(set(list(lstm_df.index) + list(prophet_df.index) + list(arima_df.index)))
    combined_df = pd.DataFrame(index=dates)
    # Adding LSTM predictions
    combined_df['LSTM_Open'] = np.nan
    combined_df['LSTM_Close'] = np.nan
    for date in lstm_df.index:
        if date in combined_df.index:
            combined_df.loc[date, 'LSTM_Open'] = lstm_df.loc[date, 'Predicted Open']
            combined_df.loc[date, 'LSTM_Close'] = lstm_df.loc[date, 'Predicted Close']

    # Adding Prophet predictions
    combined_df['Prophet_Open'] = np.nan
    combined_df['Prophet_Close'] = np.nan
    for date in prophet_df.index:
        if date in combined_df.index:
            combined_df.loc[date, 'Prophet_Open'] = prophet_df.loc[date, 'Predicted Open']
            combined_df.loc[date, 'Prophet_Close'] = prophet_df.loc[date, 'Predicted Close']

    # Adding ARIMA predictions
    combined_df['ARIMA_Open'] = np.nan
    combined_df['ARIMA_Close'] = np.nan
    for date in arima_df.index:
        if date in combined_df.index:
            combined_df.loc[date, 'ARIMA_Open'] = arima_df.loc[date, 'Open_Predicted']
            combined_df.loc[date, 'ARIMA_Close'] = arima_df.loc[date, 'Close_Predicted']

    # Calculating statistics
    stats_df = pd.DataFrame({
        'LSTM_Open_Mean': [combined_df['LSTM_Open'].mean()],
        'LSTM_Open_Std': [combined_df['LSTM_Open'].std()],
        'LSTM_Close_Mean': [combined_df['LSTM_Close'].mean()],
        'LSTM_Close_Std': [combined_df['LSTM_Close'].std()],
        'Prophet_Open_Mean': [combined_df['Prophet_Open'].mean()],
        'Prophet_Open_Std': [combined_df['Prophet_Open'].std()],
        'Prophet_Close_Mean': [combined_df['Prophet_Close'].mean()],
        'Prophet_Close_Std': [combined_df['Prophet_Close'].std()],
        'ARIMA_Open_Mean': [combined_df['ARIMA_Open'].mean()],
        'ARIMA_Open_Std': [combined_df['ARIMA_Open'].std()],
        'ARIMA_Close_Mean': [combined_df['ARIMA_Close'].mean()],
        'ARIMA_Close_Std': [combined_df['ARIMA_Close'].std()],
    })

    return combined_df, stats_df

combined_forecasts, forecast_stats = compare_forecasts(futureLSTM_df, futureProphet_df, futureARIMA_df)

# Displaying statistical summary
print("Statistical Summary of 30-Day Forecasts:")
print(forecast_stats)

# Creating a table showing model volatility comparison
print("\nForecast Volatility (Standard Deviation):")
volatility_comparison = pd.DataFrame({
    'Model': ['LSTM', 'Prophet', 'ARIMA'],
    'Open Price Volatility': [
        forecast_stats['LSTM_Open_Std'].values[0],
        forecast_stats['Prophet_Open_Std'].values[0],
        forecast_stats['ARIMA_Open_Std'].values[0]
    ],
    'Close Price Volatility': [
        forecast_stats['LSTM_Close_Std'].values[0],
        forecast_stats['Prophet_Close_Std'].values[0],
        forecast_stats['ARIMA_Close_Std'].values[0]
    ]
})
```

```
print(volatility_comparison)

# Calculating percent differences between models

print("\nPercent Differences Between Models (based on mean forecasts):")
lstm_prophet_open_diff = abs(forecast_stats['LSTM_Open_Mean'].values[0] - forecast_stats['Prophet_Open_Mean'].values[0]) /
forecast_stats['LSTM_Open_Mean'].values[0] * 100
lstm_arima_open_diff = abs(forecast_stats['LSTM_Open_Mean'].values[0] - forecast_stats['ARIMA_Open_Mean'].values[0]) /
forecast_stats['LSTM_Open_Mean'].values[0] * 100
prophet_arima_open_diff = abs(forecast_stats['Prophet_Open_Mean'].values[0] - forecast_stats['ARIMA_Open_Mean'].values[0]) /
forecast_stats['Prophet_Open_Mean'].values[0] * 100

lstm_prophet_close_diff = abs(forecast_stats['LSTM_Close_Mean'].values[0] - forecast_stats['Prophet_Close_Mean'].values[0]) /
forecast_stats['LSTM_Close_Mean'].values[0] * 100
lstm_arima_close_diff = abs(forecast_stats['LSTM_Close_Mean'].values[0] - forecast_stats['ARIMA_Close_Mean'].values[0]) /
forecast_stats['LSTM_Close_Mean'].values[0] * 100
prophet_arima_close_diff = abs(forecast_stats['Prophet_Close_Mean'].values[0] - forecast_stats['ARIMA_Close_Mean'].values[0]) /
forecast_stats['Prophet_Close_Mean'].values[0] * 100

print(f"LSTM vs Prophet (Open): {lstm_prophet_open_diff:.2f}%")
print(f"LSTM vs ARIMA (Open): {lstm_arima_open_diff:.2f}%")
print(f"Prophet vs ARIMA (Open): {prophet_arima_open_diff:.2f}%")
print(f"LSTM vs Prophet (Close): {lstm_prophet_close_diff:.2f}%")
print(f"LSTM vs ARIMA (Close): {lstm_arima_close_diff:.2f}%")
print(f"Prophet vs ARIMA (Close): {prophet_arima_close_diff:.2f}%")

# Ploting the distribution of forecasts
plt.figure(figsize=(14, 10))

# Subplot for Open Price distribution
plt.subplot(2, 1, 1)
plt.hist(combined_forecasts['LSTM_Open'].dropna(), alpha=0.5, bins=10, label='LSTM Open')
plt.hist(combined_forecasts['Prophet_Open'].dropna(), alpha=0.5, bins=10, label='Prophet Open')
plt.hist(combined_forecasts['ARIMA_Open'].dropna(), alpha=0.5, bins=10, label='ARIMA Open')
plt.title('Distribution of Open Price Forecasts', fontsize=16)
plt.xlabel('Forecasted Price', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.legend()
plt.grid(True, linestyle='--', alpha=0.7)

# Subplot for Close Price distribution
plt.subplot(2, 1, 2)
plt.hist(combined_forecasts['LSTM_Close'].dropna(), alpha=0.5, bins=10, label='LSTM Close')
plt.hist(combined_forecasts['Prophet_Close'].dropna(), alpha=0.5, bins=10, label='Prophet Close')
plt.hist(combined_forecasts['ARIMA_Close'].dropna(), alpha=0.5, bins=10, label='ARIMA Close')
plt.title('Distribution of Close Price Forecasts', fontsize=16)
plt.xlabel('Forecasted Price', fontsize=12)
plt.ylabel('Frequency', fontsize=12)
plt.legend()
plt.grid(True, linestyle='--', alpha=0.7)

plt.tight_layout()
plt.show()
```