Daily AAPL Closing Price Forecasting: A Post-Market Stock Strategy

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Introduction

Algorithmic trading advances rapidly as the ever-evolving fields of machine learning and artificial intelligence become more prominent in the strategies of financial institutions, hedge funds, and individual investors alike. These technologies enable more accurate predictions, faster decision-making, and adaptive systems that respond to complex market dynamics. One strategy useful to both intra-day and inter-day traders is the use of post-market analysis. In this project, we aim to explore predictive models that can potentially be used to simulate a real trading system in which close price, along with other technical indicators of that day, is used to forecast the following day(s) closing price(s).

Problem Statement

In this project, a scenario is set up to highlight the real-world application of our predictive models. A junior quantitative analyst on a trading team at a hedge fund that specializes in short-term equity strategies is tasked with focusing on swing trades. Swing trades are positions that are held from days to weeks. The portfolio manager wants to capture the trends in movements of AAPL (Apple) stock to time their entries and exits more efficiently, so the goal of the junior quantitative analyst is to predict short-term price direction in order to help inform daily trading decisions based on historical and recent behaviors of the AAPL stock.

With this goal in mind, four different models are trained and tested on Q1 before picking a final model based on a comparison of evaluation metrics. The selected model is then retrained daily (post market close) to forecast the next day’s closing price, allowing the team to update their outlook and adjust positions with each trading day. This approach emphasizes responsiveness and keeps the strategy aligned with the most recent market behavior.

Methodology

First, four models are chosen to be explored to understand which models best capture the nature of AAPL stock's movement and patterns. As stated previously, these models are: LSTM, CNN, ARIMAX, and Extreme Gradient Boosting. Each model has significantly different parameters and functionalities. With this in mind, each model is trained on different timeframes of historical data, but each model's training data includes data up to December 31st, 2024.

All data, both training and testing, is downloaded from the Yahoo Finance library in Python. In addition to the Low, High, Open, Close, and Volume of the stock (directly downloaded from Yahoo Finance), feature engineering is used to generate the 14-day Relative Strength Index (RSI), the previous day's closing price, the percent change from the previous day's closing price, and the 5- and 10-day moving averages. These features, available after market close, are used to predict the next day's closing price — the target variable of this project. Each of the four models is trained on these features. It is important to note that each model uses a different combination of these features based on performance during the training phase and testing on Q1 daily closing prices. This process of selecting the most optimal features for each model is expanded on in their respective sections of this report.

After tuning hyperparameters and evaluating performance on Q1 daily closing prices, these static models are compared using the following metrics: Root Mean Squared Error (RMSE), Mean

Absolute Error (MAE), R-Squared, and Directional Accuracy. The model demonstrating the strongest overall performance across these metrics is then chosen to undergo daily retraining post market close in order to most accurately forecast the coming day's AAPL stock closing prices.

Based on these results, the chosen model is retrained daily to forecast daily Q1 closing prices, and its new evaluation metrics are reviewed to highlight its improvement from being static after December 2024 to now being used for a rolling forecast. Only one model is retrained daily to maintain efficiency, as conducting a rolling forecast is more computationally expensive. After recording the model's new performance metrics, it is used to forecast the closing prices from April 7th through April 10th and determine the optimal day to sell within the next four days. This four-day forecast is chosen to simulate a short-term holding decision window, typical for swing or short-horizon trading strategies.

Long Short-Term Memory RNN

The Long Short-Term Memory (LSTM) model is selected for this project due to its strength in modeling sequential time series data. Unlike traditional models, LSTMs are specifically designed to retain long-term information, making them well-suited for stock price forecasting.

After much manual trial and error, the LSTM performs best when learning from 60-day sequences of historical stock features—including the previous day's closing price, 5-day and 10-day moving averages, daily percent return, and the 14-day Relative Strength Index (RSI). The architecture consists of two stacked LSTM layers (128 and 64 neurons), followed by two dense layers (25 neurons and a single output for the predicted close). Training is conducted over 10 epochs with a batch size of 1—a choice made to better adapt the model to daily fluctuations in volatile stock data. This small batch size allows the model to better capture the volatile nature of stocks like APPL and react faster to sharp rises and falls in price.

Once trained on data up to December 31, 2024, the model's performance on Q1 2025 is evaluated. The LSTM achieves an RMSE of 4.25, an MAE of 3.43, an R-squared of 0.829, and a directional accuracy of 50.12%. While the LSTM effectively captures AAPL's overall trend during stable periods, it tends to underreact to sharp price movements, resulting in a lower directional accuracy compared to other models in the study. This suggests that while LSTMs can provide solid baseline forecasts, they may require additional tuning (e.g., shorter RSI windows or more responsive inputs) to fully capitalize on volatile market behavior. Directional accuracy is extremely important in stock price prediction, so future improvements made to this model prioritize further feature and architecture optimization to improve its ability to capture and forecast sharp price movements.

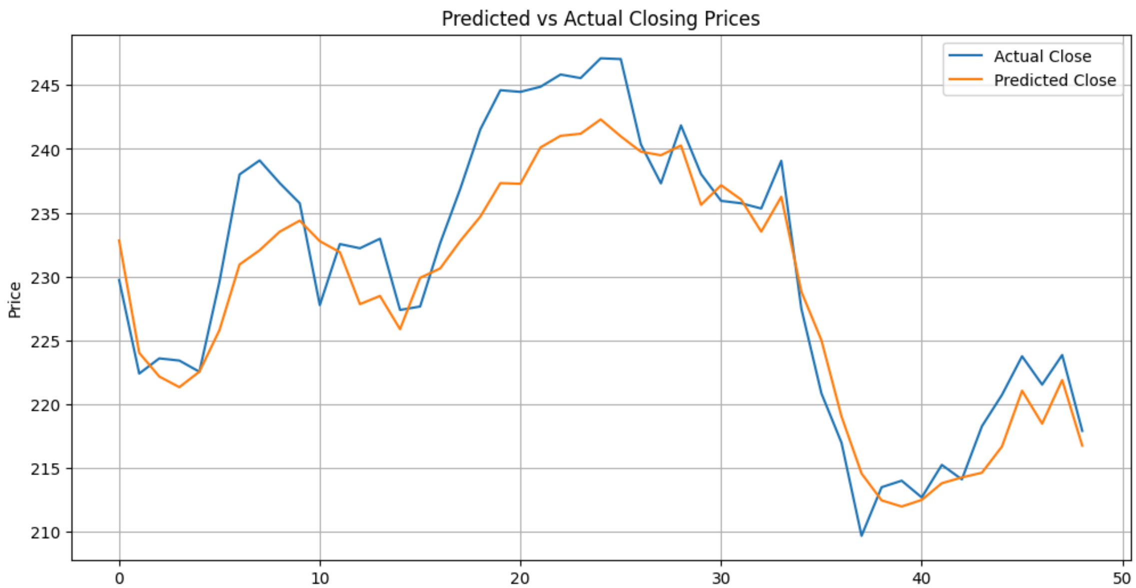
Despite this limitation, LSTMs remain a popular tool in stock forecasting due to their strong performance in sequence modeling and ability to capture various trends across different time periods.

Convolutional Neural Network

While CNN (Convolutional Neural Network) models are generally used for image analysis, one dimensional CNNs take in data sequentially due to the way the filter passes over the data. As the layers look at small local regions of data, CNNs are good at capturing short-term patterns. This can be preferable as stocks are constantly changing given the countless factors that contribute to them including something the president says, natural disasters, foreign politics, inflation, and consumer spending.

The CNN model was trained on two years of data, 2023 and 2024. The engineered features include closeLag1, openLag1, highLag1, lowLag1, and volumeLag1, the close price, open price, highest price, lowest price, and number of shares from the previous trading day respectively. Also included in the model is closeMoveAvg5, the 5 trading day rolling average of close, dailyPercChange, the daily percent change between open and close, and momentum10, the difference in the current close price and the close price 10 trading days ago. The CNN consists of a 1-dimensional convolutional layer, flatten layer, dense layer, dropout layer, and another dense layer. It runs 25 epochs with a batch size of 32.

In hyperparameter running, it was found that a smaller number of filters not only made the model run faster, but also improved results. With 32 filters, the coefficient of determination went up to 0.88, as compared to 0.79 for 64 filters. The MAE of 3.03 represents an on-average difference of $3.03 between the predicted and actual stock price. The RMSE is slightly higher at 3.64, but still suggests good performance from the model. While the directional accuracy was slightly higher with 64 filters at 81%, given the increase in other metrics, 32 filters still gave a respectable 77% accuracy. These promising results show that a model looking at short-term patterns, such as CNNs, may be the way to go for modeling stocks.



ARIMAX

The ARIMAX (AutoRegressive Integrated Moving Average with Exogenous Variables) model was used to forecast the daily closing prices of AAPL, incorporating both historical price trends and external market indicators. Unlike a standard ARIMA model, ARIMAX allows for additional inputs—known as exogenous variables—which can significantly enhance forecasting accuracy in financial time series. For this project, the exogenous features included lagged volume (Volume_lag1), lagged high and low prices (High_lag1, Low_lag1), and moving averages (MA_5, MA_10). These features were chosen based on their relevance to technical analysis and their potential to capture market sentiment and volatility.

The model was configured with an order of (2, 1, 1), meaning it used two lagged values of the differenced series, first-order differencing to achieve stationarity, and one lagged forecast error for correction. All features, along with the target variable, were standardized to ensure balanced contributions during model training. Data from January 2020 through December 2024 was used to train the model, covering various market conditions, including periods of high volatility and trend reversals.

To optimize the ARIMAX configuration, a grid search over possible (p, d, q) values was conducted, and the selected parameters provided the lowest Root Mean Squared Error (RMSE) while maintaining a low Akaike Information Criterion (AIC). The model was then evaluated on Q1 2025 data, yielding an RMSE of 4.47, a Mean Absolute Error (MAE) of 3.45, and an R-squared value of 0.81, indicating that it explained a substantial portion of the variance in price movements. Additionally, the model achieved a directional accuracy of 67.24%, successfully predicting the correct direction of daily price changes in over two-thirds of cases. Overall, ARIMAX provided valuable insights through its interpretable structure and effective use of market-based exogenous features.

Extreme Gradient Boosting

Extreme Gradient Boosting (XGBoost) is a powerful ensemble learning algorithm known for its speed, performance, and ability to handle complex, non-linear relationships in data. It builds an ensemble of weak learners,decision trees, where each successive tree attempts to correct the errors of its predecessor through gradient descent optimization. This method is particularly effective for financial time series forecasting, where patterns are often noisy, subtle, and nonlinear.

In this project, XGBoost was selected due to its proven effectiveness in structured data problems, including stock price prediction. In this project two XGBoost models were trained: a Static

Model and a Rolling Forecast Model. Feature engineering was heavily utilized to enrich the model's inputs beyond basic stock prices. Features included 5- and 10-day moving averages, lagged close prices (1 to 5 days), 1-day percent return, lagged open/high/low/volume values, and the 14-day Relative Strength Index (RSI). These features capture both momentum and mean-reversion signals commonly exploited in quantitative trading.

Both models were initially trained with 100 estimators and configured for squared error minimization. The first model was a static model using historical AAPL stock data up to December 31, 2024. What made this model "static" is that it was only trained up to Dec 2024, and from there it predicted Q1 2025 Apple stock prices. When evaluated on Q1 2025 static data, the XGBoost model achieved an RMSE of **3.41**, an MAE of **2.62**, an R^2 score of **0.89**, and a directional accuracy of **67.8%**. These results indicated strong predictive power not only in minimizing raw error but also in correctly forecasting the direction of price movements—an essential aspect of trading profitability.

To improve adaptability and mimic real-world trading systems, a second model was created, with a rolling forecast approach. After each trading day, the model was retrained with all available data up to that point, and then it forecasted the next day's closing price. This daily retraining process allowed the model to continually update its understanding of the market, reflecting the most recent behavior patterns and adapting to short-term changes in volatility and trend.

The rolling forecast version of XGBoost showed even stronger results during Q1 2025, achieving an RMSE of **2.57,** an MAE of **4.20**, an R^2 score of **0.93**, and a directional accuracy of **80.6%**. These improvements highlight the importance of continuously updating the model, especially in a dynamic market environment like equities trading.

Additionally, the model was used to generate forward-looking forecasts for April 14–19, 2025, providing hypothetical closing prices based on the rolling forecast strategy. This exercise simulated how a trading team could leverage model predictions to make daily or multi-day holding decisions in a short-term swing trading framework.

Overall, Extreme Gradient Boosting demonstrated robust predictive capabilities and high responsiveness to new data, making it a strong candidate for incorporation into a quantitative trading pipeline. Its ability to handle a wide array of technical indicators, along with its superior performance under both static and rolling conditions, positioned XGBoost as one of the top-performing models evaluated in this project.

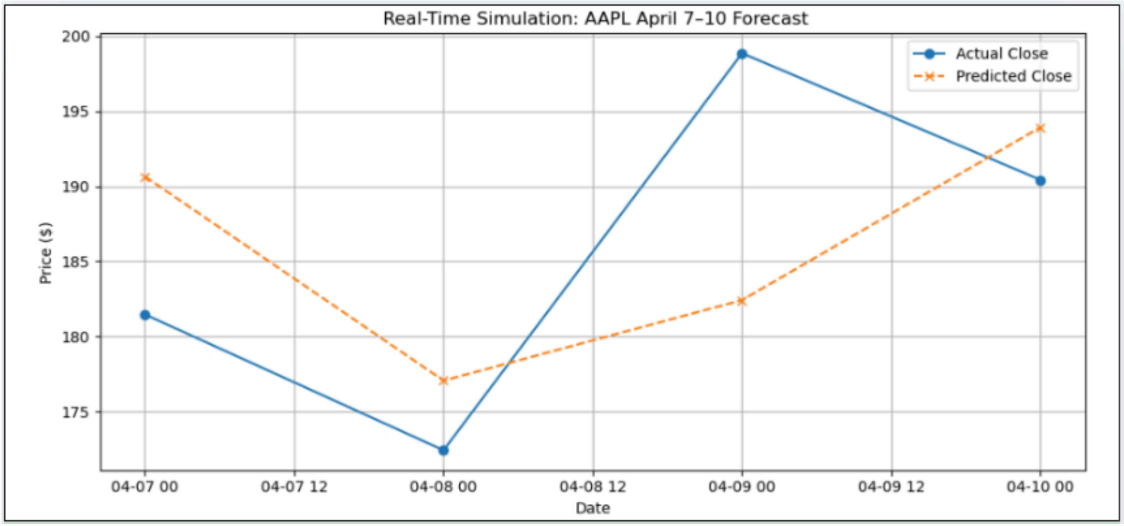
Results and Findings

The following table gives the performance of the daily Q1 closing price forecasting for each of the four static models:

	RMSE	MAE	R-Squared	Directional Accuracy
LSTM	4.40	3.44	0.82	50.12%
CNN	3.64	3.03	0.88	77.08%
ARIMAX	4.47	3.45	0.81	67.24%
XGBoost	3.41	2.62	0.89	67.80%

Using this array of performance evaluation metrics allows for a thorough comparison of the models' forecasts. However, it is worth noting the importance of directional accuracy in the context of stock price prediction. Knowing whether the stock's price will rise or fall the next day is imperative for effective entry and exit decision-making. For example, the CNN model has the best directional accuracy of 77.08%—meaning that it predicts the direction of the stock's price movement correctly 77.08% of the time when forecasting Q1 closing prices. While directional accuracy is important for forecasting short-term price movements to better time entries and exits., the error between predicted and actual prices is important to make accurate price predictions for portfolio valuation and risk management. While the CNN model has the best directional accuracy, XGBoost has the smallest RMSE and MAE, as well as the largest R-Squared. It better reflects the stock trends making it more valuable for long-term investment strategy. XGBoost is more robust and less computationally expensive than CNN. Thus, XGBoost was chosen to be used for daily retraining moving forward.

After performing daily retraining with XGBoost, its new performance metrics on the forecasting of Q1 closing prices are recorded to highlight the improvement from using a rolling forecast. XGBoost's performance improves significantly, achieving an RMSE of 2.57, MAE of 1.86, R-Squared of 0.94, and directional accuracy of 81.36%. This improvement highlights the benefit of allowing the model to learn from the most recent market behavior, adapting to short-term shifts more effectively than a static model. The plot below (April 7–10 real-time simulation) visually demonstrates how the model's predictions track the actual closing prices. Even when the price levels differ, the direction of movement is correctly captured in most cases, which is what truly matters in a trading context focused on short-term momentum.



For example, after the market closed on April 8, the analyst retrained the model and received a forecast indicating that AAPL's price would increase on April 9. Acting on this information, the analyst could decide to hold the position overnight or even consider buying in anticipation of an upward move, rather than selling into weakness on April 8. This decision would have proven successful, as the actual close on April 9 spiked significantly.

By retraining daily, the model continuously adapts to the most recent market behavior, giving the analyst fresh insight each evening to help guide next-day trading decisions, rather than relying on static, outdated signals. This setup closely mirrors how professional trading desks adjust positions day-by-day in response to changing market conditions.

Tools and External Libraries Used

The Yahoo Finance API (known as yfinance) in Python was used to download the Apple stock data (AAPL).

Team Contributions

Sidney Christensen completed the LSTM, Brianna Castano completed the CNN, Emma Kozlowski completed the ARIMAX model, and Juliana Steele completed the XGBoost model. Evaluations and conclusions drawn were made collectively as a group.

Conclusion and Future Work

To recap, this project explored four predictive models—LSTM, CNN, ARIMAX, and Extreme Gradient Boosting—to forecast AAPL's next-day closing price. Each model was trained on historical data with engineered technical features and evaluated on Q1 2025 performance. Among the models, CNN had the best directional accuracy, but XGBoost outperformed the others, achieving the best results across RMSE, MAE, R-squared, while having a respectable directional accuracy, making it the most suitable choice for daily retraining. These findings underscore the importance of combining both accuracy and adaptability in financial time series models, especially when the objective is short-term trading.

For future work, model performance could be further enhanced by incorporating external market data. Integrating real-time trading volume, macroeconomic indicators, news sentiment, and earnings announcements could help models better anticipate sharp movements not captured by historical prices alone. Additionally, modifying feature windows (such as using a shorter RSI window) may increase sensitivity to short-term trends. Exploring ensemble techniques that combine multiple models, or adding options market data and after-hours movement, could lead to even more robust and timely predictions. These improvements would bring the forecasting approach closer to what real-world trading desks require to make informed, daily investment decisions.

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