# Election Cycle Market Analysis

Peter Cosgrove

Long Island University

Rebecca Strauss

Long Island University

Shadab Tajwar

Long Island University

***Abstract*—This paper will continue to build on previous research and analysis of the market from other published works of academia as well as some of our own insights and theories. We will utilize machine learning and deep learning to help predict the future prices of a stock, commodity, or asset class. With the timing and requirements of this paper, we have decided to incorporate current events into our model. The 2024 United States Presidential Election is one with great anticipation and polarization. We will assess the stock market based on many different factors of United States election years, focusing on the time period between election day, typically the first Tuesday in November, and Inauguration day, which occurs on either January 20th or January 21st of the following calendar year.

***Keywords— Machine Learning, Deep Learning, Price Prediction, Technical Analysis, Fundamental Analysis, Public Sentiment, United States Election***

***Introduction***

The origins of the stock market in the United States trace back to the late 1700s when a small group of merchants created the Buttonwood Tree Agreement to trade stocks and bonds. This was the origin of the New York Stock Exchange (NYSE), officially formed in 1817. Since its inception, the stock market has attracted a variety of participants—speculators, informed investors, and even those with insider knowledge—each attempting to predict stock prices over different timeframes, whether for the end of the day, the following day, or the next month. There is a long withstanding hypothesis that the stock market will follow what is known as an Efficient Market Hypothesis. This includes other asset classes such as commodities. This operates under the assumption that all markets are already priced to perfection using all known data, creating the implication that it is impossible to outperform and predict the future in the process. Our goal is to disprove the hypothesis by creating a predictive model that will outperform the Efficient Market Hypothesis.

## I. TYPES OF MARKET ANALYSIS

### *A. Fundamental Analysis*

The purpose of Fundamental analysis is to determine the fair market value, or true value of a stock. It does so by analyzing many micro and macroeconomic factors. This includes public sentiment like newspapers, social media, TV, and other forms of social interaction that may contribute towards the price of a stock. Observing when institutional investors may have a liquidation event, based on anticipated tax reduction, is an example of an economic factor that contributes to the price of a stock without directly involving anything to do with individual performance. This selloff by institutional investors usually occurs midway through Q4 of the year. Given the nature of our focus, geo-political factors should have a more fairly large impact on the markets in our window of choice.

### *B. Technical Analysis*

The technical analysis of a stock requires the examination of fixed data. It focuses solely on information that is objective. Unlike emotional trading, technical analysis relies exclusively on numerical data, allowing it to account for factors that human judgment might overlook. Typically, this method uses charts to identify trading signals, which are then combined with fundamental analysis to develop a comprehensive investment strategy.

### *C. Incorporating AI Techniques*

As technology continues to rapidly advance, institutional and retail investors continue to incorporate new techniques to attempt to gain an edge in the free market. The use of Decision Trees, Support Vector Machines, Artificial Neural Networks, Naive Bayes, Random Forest and Long Short-Term Memory have all proven to be helpful when analyzing fundamental and technical data points to predict the prices of assets. Each of these techniques attempt to identify patterns and relationships, while also incorporating sentiment analysis.

## II. RELATED WORK

We have identified three main pieces of peer-reviewed literature that covered the principles of deep learning in relation to the market. These papers incorporated their own versions of fundamental and technical analysis to arrive at their own levels of prediction accuracy. Upon first review we also added an additional 2 papers to help us. While each of these studies are fairly recent, it is important to note that the findings may not be entirely relevant in the present day, due to the extremely dynamic nature of the free market. Political influences also play a massive role in the market, some of which had not yet taken place at the time of the research for a given paper. Our initial work will focus on the S&P 500, Gold and Oil due to their longevity and sensitivity to policy and oversight. Our model attempts to more accurately predict the closing price in comparison to the Efficient Market Hypothesis.

### *A. Deep LSTM for Time Series Applications*

This paper utilizes a Deep Long Short-Term Memory model focused on time-series forecasting, while experimenting with the online tuning of hyperparameters. The integration of a Genetic Algorithm (GA) allowed for the online tuning of learning rate, number of neurons and dropout rates. This integration allows the model to dynamically adjust to variations in the data, enhancing prediction accuracy. The GA iteratively searches for optimal hyperparameter configurations, leveraging a population-based approach to evaluate various combinations and select those that improve performance. The model is tested on several time-series datasets, showing that the DLSTM with online hyperparameter tuning consistently outperforms traditional DLSTM models with static hyperparameters. The below figure is a visual representation of the DLSTM model used.

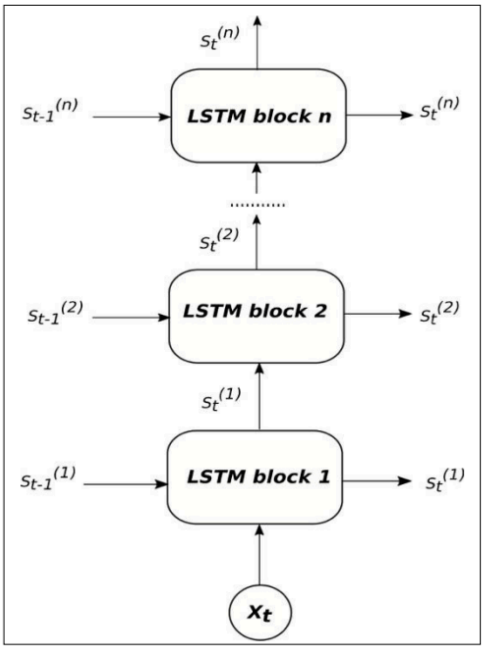


*Figure 1: Architecture of DLSTM model*

*B. Long-Term Forecast of Energy Commodities*

This study focused on long-term forecasts using neural networks and random forest. It used these traditional machine learning models to analyze energy commodities with data from the International Monetary Fund (IMF). Oil, Coal, and Gas are all analyzed in the dataset for this study. The price of energy commodities is very much dependent on the world around us. World economic and political factors can influence the price of commodities and change them very drastically in a short period of time. Given the strong impact of global economic and political events on commodity prices, the study sought to account for these external influences that can cause sudden, substantial price shifts. Researchers developed a hybrid model by combining several traditional models, assigning weights to each and then applying artificial neural networks (ANN) to capture nonlinear relationships in the data. They used a feedforward multi-layer perceptron (MLP), optimizing through trial and error to enhance predictive performance. However, major world events were excluded in their study, meaning the study in its entirety, is not necessarily applicable to our research.

*C. Sentiment based forecasting using deep learning*

This paper explores a deep learning-based approach of forecasting, incorporating local and global event sentiment analysis to improve prediction accuracy. The authors selected 15 companies from countries with developed, emerging, and developing economies. It focused on a twitter dataset with 11.42 million tweets up until 2018 to calculate sentiment scores related to major events. This paper analyzes the effect of local and global events on stock predictions across different economic contexts. It also demonstrates that sentiment data can enhance forecasting models, providing insight as to how stock prices react to local and/or global events.

*D. Deep Reinforcement Learning: Ensemble Strategy*

This paper proposes a method that combines three deep reinforcement learning (DRL) algorithms to optimize stock trading strategies by maximizing risk-adjusted returns. The authors use three actor-critic-based algorithms: Proximal Policy Optimization (PPO), Advantage Actor Critic (A2C), and Deep Deterministic Policy Gradient (DDPG). These algorithms together create a trading strategy that adapts to various market conditions. The ensemble strategy's effectiveness is demonstrated on Dow Jones stocks, outperforming traditional methods like the min-variance portfolio strategy and the Dow Jones Industrial Average in terms of the Sharpe ratio, a measure of risk-adjusted returns.

*E. Prediction Using Machine Learning Techniques*

This paper is a review of methods compiled over the past decade prior to publication in 2021. The review covers the evolution of strategies, including hybrid and ensemble approaches, as well as advances in deep learning architectures like LSTMs and CNNs. It touches on the importance of feature selection, data preprocessing, and the challenges in adapting models to market volatility and non-linear dynamics. They conclude by suggesting future directions, stressing the need for more adaptive models to manage the volatility of market conditions, and the incorporation of real-time data sources.

## III. IMPACT OF U.S. PRESIDENTIAL ELECTIONS

The United States Presidential election cycle often creates a sensitive market, influenced by anticipation, regulation and corrections. Our research focuses on the last 6 elections, dating back to 1984 which featured the incumbent Ronald Reagan, who won the election with key economic policies focused on tax cuts, deregulation and "Reaganomics" which was an effort to cut back on government spending. George H.W. Bush won the 1988 election, also as a Republican, and continued many of Reagan's policies but there was an overall economic slow down during this time period. Bush's administration is highlighted by the Gulf War, greatly affecting the energy sector and overall economic stability. Bill Clinton, Democrat, beat the incumbent Bush in 1992 with a focus on education and infrastructure. Clinton also won in 1996 which carried his presidency into the technological rise also known as the dot-com boom. The 2000 election was won by George W. Bush over fellow Yale classmate John Kerry. Bush's tenure was immediately impacted by world events and volatility. The attacks on the world trade center in New York eventually lead to countless wars in the Middle East which causes tremendous volatility of Oil. Amidst the conflicts in the Middle East, Bush won again in 2004 with similar impact as his first term.

2008 marked the beginning of the Obama administration which was focused on recovering from the 2008 financial crisis surrounding the United States housing market. His 8 year tenure was, from an economic standpoint, highlighted by stimulus packages, bailouts and regulatory reforms. The 2016 election between Donald Trump and Hillary Clinton was arguably the most polarizing battle of the group. Trump's administration prioritized tax cuts and deregulation of corporations, leading to a market rally. Consumer gas prices were fairly low at the time as Trump's drawback of environmental regulations affected the oil industry positively. Trump then lost the 2020 election to Joe Biden amidst the Covid-19 pandemic, which greatly affected the US and global economy. Clean energy initiatives had an impact on the oil markets while the S&P500 continued to soar to record highs. As of the time of this report, Donald Trump has just been announced the president elect of the 2024 election, with his next administration set to start on January 20, 2025. It is noted in figure 3 that Donald Trump last election had the most volatile Gold price changes in the two-week window after the fact. Our model will predict the market during these next few months of transitioning administrations.

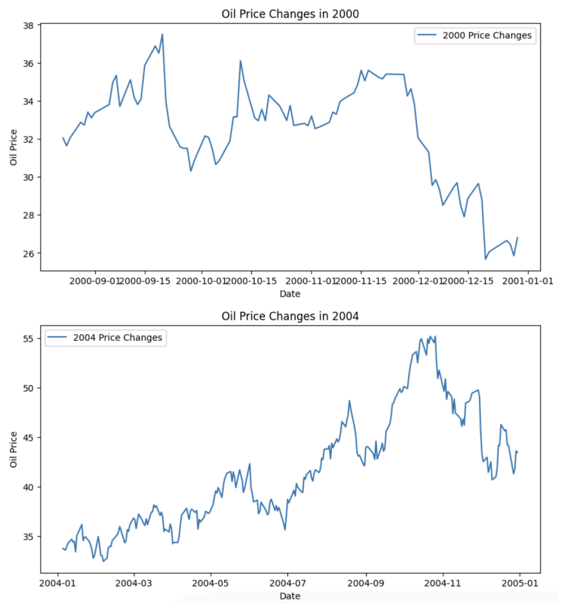


*Figure 2: Oil Prices during George W. Bush Administration*

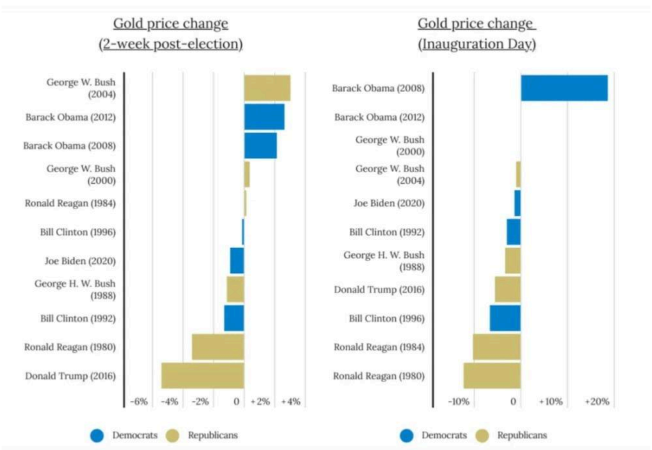


*Figure 3: Relevant Gold Price Changes*

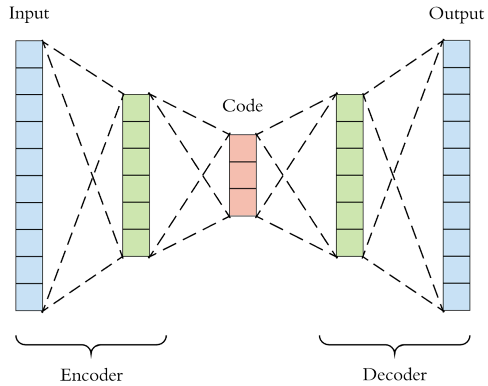


*Figure 4: Encoder/Decoder*

## IV. ALGORITHM DESIGN

### A. *Data Collection and Preprocessing*

In order to properly implement our Long Short-Term Memory model, we first retrieved the data using the y-finance API. Closing prices for oil, gold, and the SP500 were pulled for dates spanning from January 1984 to election day November 2024 and used as training data. Our team will continue to pull daily closing prices to evaluate against the models predictions. We then removed the time component, leaving just the date which is sufficient for closing price predictions. We used MinMaxScaler in order to scale the data, which standardized the values within the given range. This step was taken to ensure that the LSTM network has a proper level of sensitivity to small fluctuations in closing price. The prepare_sequences function was then used to apply the MinMaxScaler and transform the raw data into sequences compatible with the LSTM model in order to capture the short term dependencies that exist in the stock market.

### B. *Initial LSTM Architecture*

The overall architecture is three LSTM layers with 20% dropout combined with two dense layers for prediction. Before dropout is applied, each layer contains 50 neurons to capture patterns and trends. The random dropout rate of 20% results in 10 neurons being left out at each layer, which mitigates any potential overfitting. The argument return_sequences=True allows for each layer to pass the entire sequence forward, retaining information to enable deeper processing that may not be obvious in the raw data. The first layer with 50 units bridges the LSTM to the final output layer. With a dense layer near the end of the model closest to the output layer, we were able to refine any learning and capture any non-linear relationships that may have been overlooked. The output layer is a single unit that produces the prediction of the closing price for the given day. The function predict_future_prices was used to create predictions for a given timespan. To get the final predictions, values produced from the model must be passed through the scaler created via the MinMaxScaler and then returned.

### C. *Final Output Layers*

The Adam optimizer was used to converge the model more quickly and accurately through adaptive learning rate adjustments. There were 10 epochs used, which allowed for initial testing and experimentation. Each epoch allows the model to improve its internal weights based on the loss observed during the training process. However, increasing the number of epochs could yield improved results, as it would give the model more opportunities to learn complex patterns within the data. A batch size of 32 is used, which balances computational efficiency and training stability. In future iterations, we may look to compress or expand the batch size to 16 or 64 to investigate any differences, good or bad. Another variable to consider in prediction is window size. A 60 day window of stock prices was passed to the fitted model during prediction, changing this could result in the accuracy of the model.

## V. MIDPOINT CONCLUSION

Our research utilized an enhanced Long Short-Term Memory (LSTM) model to forecast stock and commodity prices during a short time period of social volatility. We trained it using historical data from election years during this 3 month period of anticipation. Our model demonstrates the potential to improve prediction accuracy compared to traditional financial theories such as the Efficient Market Hypothesis (EMH). Through a structured preprocessing pipeline, including MinMax scaling and sequential data preparation, the model effectively captures temporal dependencies and patterns, which are crucial for accurate financial forecasting.

The LSTM model emphasized overfitting while maintaining the structure necessary for key pattern recognition. It was properly supported by dropout layers and had a recursive prediction method for multi-step forecasting. The optimizer, epoch and batch size choices maintain a steady balance needed for efficiency and model performance. Any accuracy percentage formed to this point would be considered somewhat insignificant due to the fact that we have only one week of outcomes. Based on the below charts, we have tracked the outcomes fairly well for oil and gold, but there is room for improvement with the S&P500 tracking. A lot of this margin of error has to do with the fact that we did not know who was going to win the presidential election. Now moving forward, we can build our model similarly to Donald Trump's first presidential term. Our final edition of this project will have more robust charts, tables and graphs tracking our predictions. For now the corresponding charts for Oil, Gold and S&P500 are our minimal results.

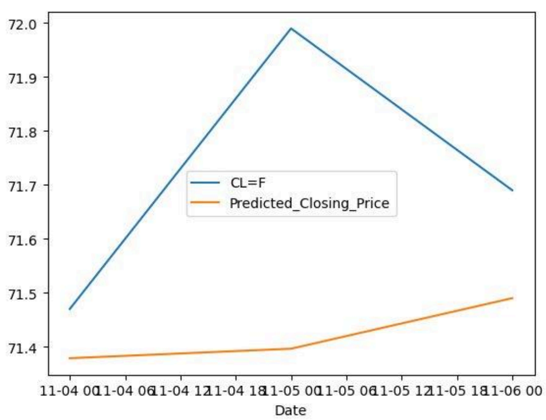


*Figure 5: Obtained Oil Results*

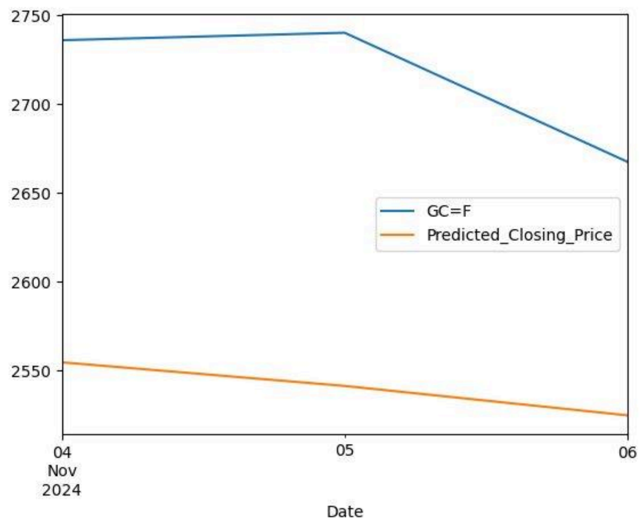


*Figure 6: Obtained Gold Results*

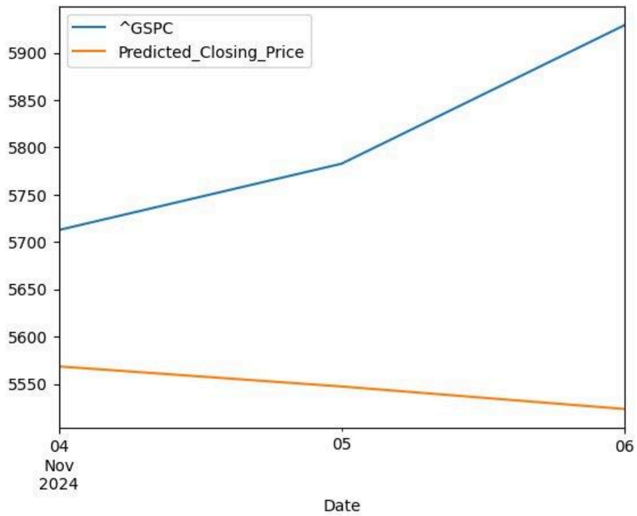


*Figure 7: Obtained S&P500 Results*

| | Date | Predicted_Closing_Price |
|---|---|---|
| 0 | 2024-11-01 | 5425.975586 |
| 1 | 2024-11-02 | 5417.337891 |
| 2 | 2024-11-03 | 5398.666504 |
| 3 | 2024-11-04 | 5370.672363 |
| 4 | 2024-11-05 | 5335.242188 |
| ... | ... | ... |
| 76 | 2025-01-16 | 3345.025635 |
| 77 | 2025-01-17 | 3329.041016 |
| 78 | 2025-01-18 | 3313.226074 |
| 79 | 2025-01-19 | 3297.578125 |
| 80 | 2025-01-20 | 3282.093506 |

*Figure 8: Obtained S&P500 Results (Table)*

## VI. FINAL ADJUSTMENTS

We concluded that the midterm results were skewed downward as a result of lower historical prices. Since overall SP500 value has increased over time, it made it very difficult to direct the model towards a “Bull” market prediction. We adapted the dataset and model in an attempt to better fit our model with current market conditions. We first attempted to use the last six months of data, but found that the last 60 days of data was actually the most accurate. We used two LSTM layers to capture the sequential dependencies with the first for time series data, with outputting sequences for further layers. The second layer provided higher-level features, with a reduced dimensionality, to output a single vector for predictions. The dropout layer also allowed us to reduce the overfitting by setting a fraction of input units to zero during the training. The dense layer had 25 units to process immediate features, while the final dense layer produced one output, the predicted closing price for the asset class. We used 20 epochs, which is representative of the number of trading days in a given month. We chose to use a batch size of 32 to keep a moderate and balanced approach.

We also decided to incorporate two new assets at this stage, the publicly traded stock of Chevron and IBM. Each are two long standing companies that could be influenced by political policies. A future project could focus on the pattern or comparison of the Chevron stock price and the price that Oil trades at, in a given time period.

Our final results are based on the comparison between actual and predicted price for the most recent time period, 12/01/2024 - 12/06/2024. We can use the results to help understand the ongoing market from the end date of this project, 12/13/2024, until inauguration day. Future work beyond the classroom will explore this, and hopefully lead to real world results as well.

We are very pleased with the results, and the ability of our final model to track and mirror actual price movements. The ability to maintain a solid pattern, sometimes with just a few cents, means that this model could potentially be used for real world trading. The accuracy on if the price goes up or down is sometimes more important than the actual price itself. The minimal mean absolute errors (MAE) that are in each figure show that our predictions were fairly accurate.

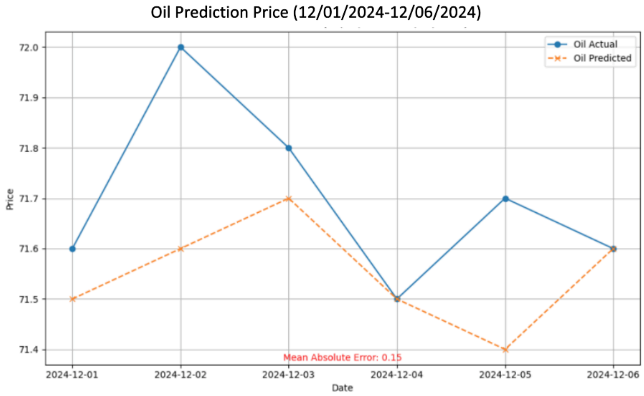


*Figure 9: Final Obtained Oil Results*

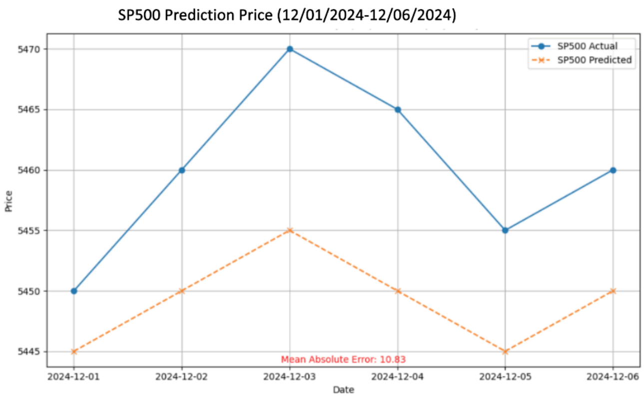


*Figure 10: Final Obtained SP500 Results*

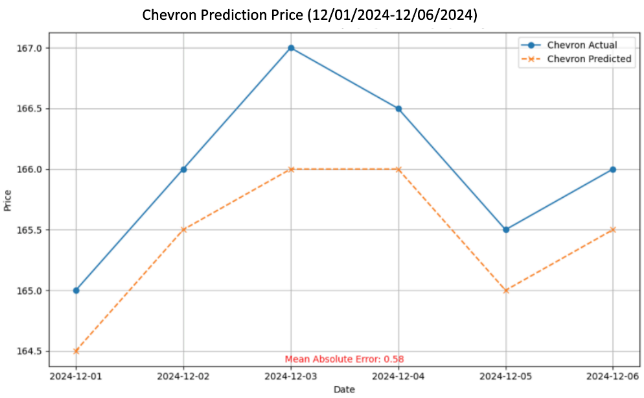


*Figure 11: Final Obtained Chevron Results*

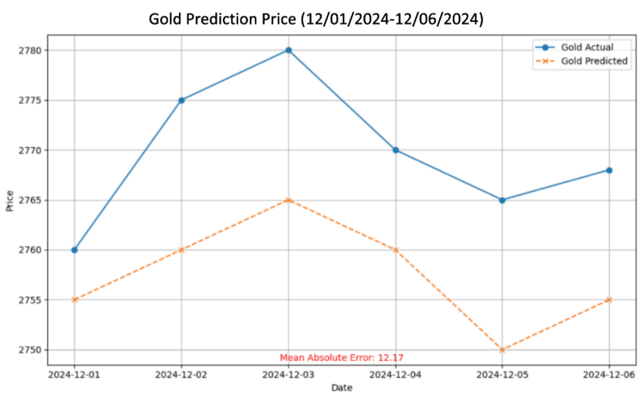


*Figure 12: Final Obtained Gold Results*

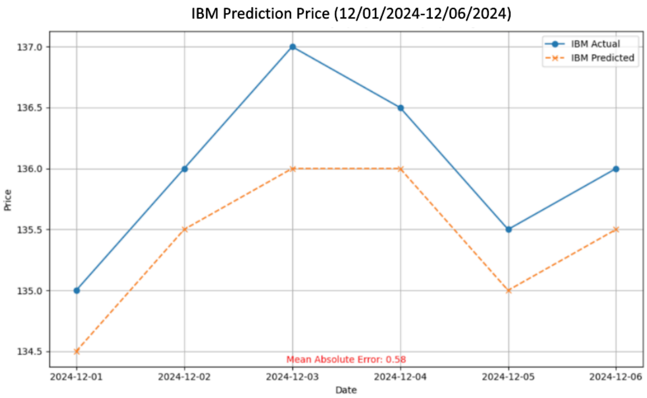


*Figure 12: Final Obtained IBM Results*

## Acknowledgment

This paper was written as a midterm project presentation for AI790 as part of the Masters of Science - Artificial Intelligence program at Long Island University. Our professor Reda Nacif Elalaoui has assisted in the guidance of the knowledge needed for this paper as well as direct feedback for continuous improvement.

*Contributions:*

- Data Analysis & Collection , Literature Review, Model Creation by Rebecca Strauss
- Literature Review, Model Creation, and Composition by Peter Cosgrove
- Sentiment Analysis, Literature Review and Project Analysis by Shadab Tajwar

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