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| RESEARCH ARTICLE

Predictive Modeling of US Stock Market and Commodities: Impact of Economic Indicators and Geopolitical Events Using Machine

MD Tushar Khan[1], Rabeya Akter[2], Hossain Mohammad Dalim[3], Abdullah AL Sayeed[4], Farhana Rahman Anonna[5], MD Rashed Mohaimin[6] and Mitu Karmakar[7]

[1]Master of Science in Business Analytics, Trine University, Angola, IN, USA
[2]Master of science in information technology. Washington University of Science and Technology, Alexandria, VA, USA
[37]School of Business, International American University, Los Angeles, California, USA
[4]Master of Business Administration in Project Management, Central Michigan University, Mt Pleasant, MI, USA
[5]Master of science in information technology. Washington University of Science and Technology, Alexandria, VA, USA
[6]MBA in Business Analytics, Gannon University, Erie, PA, USA

Corresponding Author: Mitu Karmakar, **E-mail**: iau@karmakarmitu.info

| ABSTRACT

Comprehending the dynamics of the stock market is pivotal for investors, policymakers, and economists in the USA. The United States stock market being one of the most influential financial markets in the world, contributes significantly to shaping the world economy. This research project aimed to bridge the important gaps in understanding the interrelationship between economic indicators and geopolitical events concerning the performance of the US stock market and commodities. The prime objective was to assess how different economic indicators have an impact on stock market performance over a specific period. In this regard, the development of machine learning models facilitated the ability to forecast stock market and commodities trends. These models utilized economic indicators and geopolitical events from historical data to predict future movements in the market with higher accuracy than the traditional forecasting technique followed. The study considered several different datasets to comprehensively analyze the effects that economic indicators and geopolitical events have on the stock market and commodity performances. The key datasets used in this analysis involve historical stock market indices such as the S&P 500, Dow Jones Industrial Average, and NASDAQ, as well as commodity prices for gold, oil, and silver. These datasets were collected from reputed financial databases such as Bloomberg and Federal Reserve Economic Data-FRED, for metrics including GDP growth rates, unemployment rates, inflation figures, and interest rates. The researchers also gathered data on geopolitical events: elections, trade wars, and military conflicts, using usually reliable news archives like Reuters, Bloomberg News, and The New York Times. Linear Regression, Random Forest, and XG-Boost algorithms were selected to capture various facets of the data. The performance metrics used to evaluate the models in this study included Mean Absolute Error, Root Mean Squared Error, and R-squared. Random Forest Regressor outperformed the other models with the lowest RMSE, showcasing its ability to model complex relationships. XG-Boost Regressor equally delivered a strong balance between performance and computational efficiency, achieving similar accuracy to Random Forest. Results from this study therefore can inform policy makers, especially in regards to stabilizing the financial markets during periods of heightened economic or geopolitical uncertainty. Key recommendations include developing proactive policy measures that could dampen the effect of adverse economic indicators and geopolitical events on market stability.

| KEYWORDS

Predictive Modelling; US Stock Market; Commodities; Stock Valuation; Machine Learning; Investors; Random Forest; XG-Boost

| ARTICLE INFORMATION

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1. Introduction

Background and Motivation

According to Khan et al. (2024), understanding the dynamics of the stock market is pivotal for investors, policymakers, practitioners, and economists in the USA. Being one of the most influential financial markets in the world, the United States stock market contributes much to shaping the world economy. Gurung et al. (2024), contended that among the main factors that influence the course taken by the stock market, interrelations between economic parameters should be pointed out-inflation rates, unemployment level, interest rates, and gross domestic product. These indicators are insight into the health of the economy and usually act as the depiction for investors to speculate on the possible risks and opportunities of the economy. However, Chakraborty (2023), argued that economic fundamentals alone do not drive the stock market. Geopolitical events variance in trade wars, military conflicts, and changes in political leadership also have a very strong effect on the volatility of the market, causing the bases for such change to fluctuate rather fast in manners that are highly unforeseeable. In such a scenario, where economic indicators strongly interlink with geopolitical events, the atmosphere is rather complicated, and a sudden swing in stock prices and commodity values needs an explanation of the connection between them.

Abdou et al. (2024), posited that investors are specifically interested in how these factors impact market performance because they directly affect investment returns. For the policymakers, such an understanding of the relationships would help them formulate policies that could stabilize the financial markets in periods of economic or political turmoil. Zeeshan et al. (2024), stated that the ability to predict the stock market based on economic indicators and geopolitical events is an academically interesting and practically important subject. This capability gives a possibility to elaborate risk management strategies, enabling investors to protect their portfolios from unfavorable conditions. Furthermore, Rao et al. (2024), asserted that in the context of globalization and digital finance, using advanced analytical techniques and machine learning provides an edge in accurately forecasting market trends. Machine learning models offer a sophisticated approach to analyzing large datasets, capturing intricate patterns, and making data-driven predictions that were previously beyond reach with traditional statistical methods (Shawon et al., 2024).

1.1 Objectives

This research project aims to bridge the important gaps in understanding the interrelationship between economic indicators and geopolitical events concerning the performance of the US stock market and commodities. The prime objective is to assess how different economic indicators have an impact on stock market performance over a specific period. Looking at historical data in our study, we try to identify any leading patterns that may indicate market highs or lows and focus on using such insights to assist the investor in a better optimization of their portfolios. Furthermore, the current study will investigate impactful geopolitical situations that drive volatility in markets. Events such as elections, international conflicts, and policy changes are common causes of increased uncertainty in markets. From studying the effects of the named events on the prices of securities and commodities, we would want to quantify these effects and study the underlying mechanisms that alter market stability. In this regard, the development of machine learning models would be facilitated for the ability to forecast stock market and commodities trends. These models would utilize economic indicators and geopolitical events from historical data to predict future movements in the market with higher accuracy than the traditional forecasting technique followed. We will also apply machine learning algorithms to capture nonlinear relationships and complex patterns missed by many conventional models. This study will also present ways investors can hedge against risks when the economy faces instability and geopolitical turmoil. This will involve the formulation of investment strategies resilient to market shocks that shall assist investors in protecting their assets and maximizing return in light of volatility.

2. Literature Review

2.1 Indicators of the Economy and Stock Market Performance

Numerous volumes of empirical studies have examined the association between economic indicators and stock market performance, demonstrating that macroeconomic factors play a critical role in influencing stock prices and market trends. Buiya et al. (2024), indicated that macro-economic factors are a key driving force for development in the prices of stocks and market trends. Key economic indicators that dictate the performance of stock exchange markets include GDP, inflation rate, unemployment rate, interest rate, and consumer sentiment, among others (Verma et al., 2024). It is, therefore, important to understand this relationship for investors and policymakers to make well-versed decisions in the periods that characterize economic turmoil.

A) GDP and Market Performance:

Xu et al. (2023), indicated that Gross Domestic Product, which measures the overall economic output of a nation, is a widely recognized indicator of economic health. Significant studies have demonstrated a strong correlation between GDP growth of stock market performance. Normally, an increase in the level of GDP is associated with higher corporate earnings, thereby boosting investor confidence and acting to raise the prices of stocks. For instance, Srivastava et al. (2023), established that stock returns are positively correlated with real economic activity, particularly GDP growth rates. From his investigation, he drew the implication that investors predict future economic activity, and stock prices reveal expectations of changes in GDP. This places on the stock market the burden of an assignment of having a forward-shifting indicator of economic health.

B) Inflation and Returns to Stocks:

Agyapong (2024), contended that Inflation is considered as the rate at which the general price of goods and services rises, and it has negative and positive effects on stock markets. Retrospectively, high inflation erodes purchasing power and diminishes spending by consumers and corporate profits. The negative consequence for profits can, in turn, result in lower stock prices. Gupta et al. (2024) found that inflation is one of the critical risk factors influencing stock returns. They concluded that, on the whole, surprise inflation is inversely related to stock prices because surprise inflation elicits uncertainty and affects the future cash flow of a company. There are other studies indicating that moderate levels of inflation can be beneficial for stocks, especially in those industries that can easily pass higher costs onto consumers (Sumon et al., 2024).

C) Unemployment Rates and Market Behavior:

Niu et al. (2023), reported that the unemployment rate, defined as the percentage of the labor force that is unemployed, is another relevant economic indicator to consider regarding its impact on the stock market. When unemployment rates are high, this is generally an indication of bad economic times; when there is less consumer spending, business profitability reduces. Recent studies in this area have found a negative relationship between unemployment rates and stock market returns. Rising unemployment tends to usher in bear markets since reduced consumer demand eventually hits companies' revenues and profitability (Islam et al., 2024).

D) ***Interest Rates and Stock Valuations:***

Soltani et al. (2024), indicated that the interest rates are decided by central banks to curb inflation and accelerate, or slow down the economy appropriately. It has been amply recorded how the interest rate change and the performance of the stock market relate to each other. Higher interest rates increase the cost of accessing capital; this, in turn, reduces corporate investment and consumer spending, which may hurt stock prices. On the other hand, low interest rates tend to increase stock valuations by making borrowing cheap, thus encouraging investment. Khan et al. (2024) demonstrated the effectiveness of monetary policy to be of utmost importance, with monetary policy interest rate changes' surprises increasing market volatility.

Geopolitical Events and Market Volatility

Geopolitical events add yet another layer of difficulty to stock market analysis, as most have the potential to create sudden and sometimes extreme market volatility. In particular, there is a broad set of events from wars and elections to international trade disputes and policy changes. While economic indicators tend to influence markets over a longer period, geopolitical events have an immediate consequence because of the potential disruption in both economic stability and investor sentiment (Niu et al., 2024). Wars and military conflicts are amongst those very disruptive geopolitical events that usually lead to sharp sell-offs in stock market indices as investors try to minimize their exposure to a heightened level of risk. One good example was during the Gulf War in the early 1990s when worldwide markets were seriously volatile due to the fear of supply chain disruption and increased oil prices (Debnath et al., 2024). Similarly, the setting of the COVID-19 pandemic can be considered a geopolitical event since its aftermath brought unprecedented global economic and political effects that caused unparalleled market volatility as governments across the world enforced lockdowns and travel restrictions (Chakraborty et al., 2024).

Moreover, elections and political transitions are other critical modulators of market behavior. Investors are usually apprehensive about the possibilities of changes in policies that could affect corporate profitability, tax regimes, and regulatory environments (Al-Mukaddim et al., 2024). Consider the 2016 US presidential election, where there were wild swings as investors speculated on what a Trump presidency would mean for trade policies and, subsequently, economic growth. Abdou et al. (2024) postulated that political uncertainty enhances market volatility; generally, markets have more volatility in election years.

Rao et al. (2024), elucidated that policy adjustments, such as shifts in trade agreements and monetary policy, can also have profound effects on market performance. For example, there was a very volatile performance in stock markets concerning the US-China trade war, initiated in 2018, since there was speculation about the tariffs and how they would affect global supply chains. To drive this home, case studies of historical market reactions to geopolitical events like Brexit and the annexation of Crimea by Russia took it a step further by showing how geopolitical uncertainty can sharply drop investor confidence, triggering sell-offs in both stock and commodity markets (Shil et al., 2024).

Machine Learning in Financial Forecasting

Applications of machine learning techniques to financial forecasting have recently received serious attention due to the demand for better and timely predictions in markets that have grown increasingly complex. Conventional models used in finance are of a linear assumption nature and thus cannot necessarily portray the real world of financial markets, which is nonlinear and dynamic (Solatin et al. 2024). Conversely, while machine learning tends to shine in identifying complex patterns with large data sets, it would be equally well-suited as an awesome tool for stock market and commodity predictions.

Machine Learning algorithms such as support vector machines, XG-Boost, and random forests are among the widely applied machine learning models in the stock market. These models are based on a historical perspective, finding patterns and trends within the data that could be further used for any prediction of market fluctuations. For example, research done by Sha et al. (2023) has illustrated that the application of Machine Learning models in stock price prediction is effective. These studies have proved that machine learning algorithms outperform traditional statistical models, such as the ARIMA model, in efficiency aspects. The results of Fischer and Khadka (2024), however, seemed to hold great promise for deep learning models, in particular LSTM networks, in predicting stock market returns because these capture sequential dependencies in a time series.

Other applications of machine learning are forecast predictions in the stock market, predicting various commodity prices, such as oil and gold, sensitive to economic indicators and geopolitical events. For instance, Xu et al. (2024) investigated the use of neural networks in predicting gold prices. It became apparent that the models indeed possessed strong predictability since they accounted for a range of macroeconomic variables. Moreover, the inclusion of sentiment analysis from social media and news sources has increased the predictability of machine learning models. By incorporating market sentiment analysis, machine learning algorithms provide real-time data on geopolitical developments, hence being much more responsive in their forecasts.

The review of previous studies identified the advantage of ensemble methods that combine several machine learning models by improving prediction accuracy and robustness. For instance, Zyatkov (2021) reviewed applications of ensemble learning techniques in financial forecasting and concluded that these techniques always outperformed compared to the performance obtained from a single model. Their value is more specific in the forecasting of the effects brought about by both economic and geopolitical factors on stock markets and commodities because machine learning models can process vast data and adjust to changeable real-time market conditions.

3. Data Collection and Preprocessing

3.1 Data Sources

The study considered several different datasets to comprehensively analyze the effects that economic indicators and geopolitical events have on the stock market and commodity performances. The key datasets used in this analysis involve historical stock market indices such as the S&P 500, Dow Jones Industrial Average, and NASDAQ, as well as commodity prices for gold, oil, and silver. These datasets were collected from reputed financial databases such as Bloomberg and Federal Reserve Economic Data-FRED, for metrics including GDP growth rates, unemployment rates, inflation figures, and interest rates. The researchers also gathered data on geopolitical events: elections, trade wars, and military conflicts, using usually reliable news archives like Reuters, Bloomberg News, and The New York Times. Government reports from agencies such as the BEA and the IMF were added to validate how appropriate and accurate the data supplied on the macroeconomic variables would be (Pro-AI-Robikul, 2024). In providing multi-sourced information, a very in-depth analysis was created by merging historical financial data with current real-time geopolitical events in the creation of predictive models.

3.2 Data Pre-Processing

First, the preprocessing code cleaned up the data provided in a structured manner to make it machine-learning model-ready. The code first removed unnecessary columns such as 'Unnamed: 0' (Step 1). Subsequently, the code identified numeric columns that have commas and cleaned them by removing the commas and converting them into floats-for example, commodity and stock prices (Step 2). Next, the analyst then checked for any missing values and reported the count of each (Step 3). Next, it proceeded to Step 4 by converting the 'Date' column to Date-Time format and extracting features such as 'Year', 'Month', 'Day', and 'Weekday', after which it drops the original 'Date' column since its components have been extracted. The dataset is further augmented by the creation of lag features on each column, providing the past values, for example, 1 day and 2 days, introducing some NaNs that will later be removed (Step 5). Successively, the data are scaled for normalization using Standard-Scaler (Step 6). The dataset is then split into features, X, and the target variable, 'Natural_Gas_Price', followed by a train-test split, where 80% of the data has been allocated for training and the remaining 20% for testing; Step 7. Finally, the shape of the preprocessed dataset is visualized. The code verifies all changes that have taken place (Pro-AI-Robikul, 2024). This step-by-step preprocessing ensures the information prepared is clean, scaled, and ready to use in machine learning model training.

3.3 Exploratory Data Analysis (EDA)

We conducted detailed EDA to identify key patterns:

Price Trends: Visualized the price evolution of commodities and stocks over time

Trading Volume Analysis: Highlighted trading activity levels and their fluctuations.

Volatility Analysis: Examined periods of market stability and instability using rolling standard deviations.

Correlation Analysis: Explored relationships between various assets, providing insights into potential market dependencies.

Descriptive Statistics and Data visualization

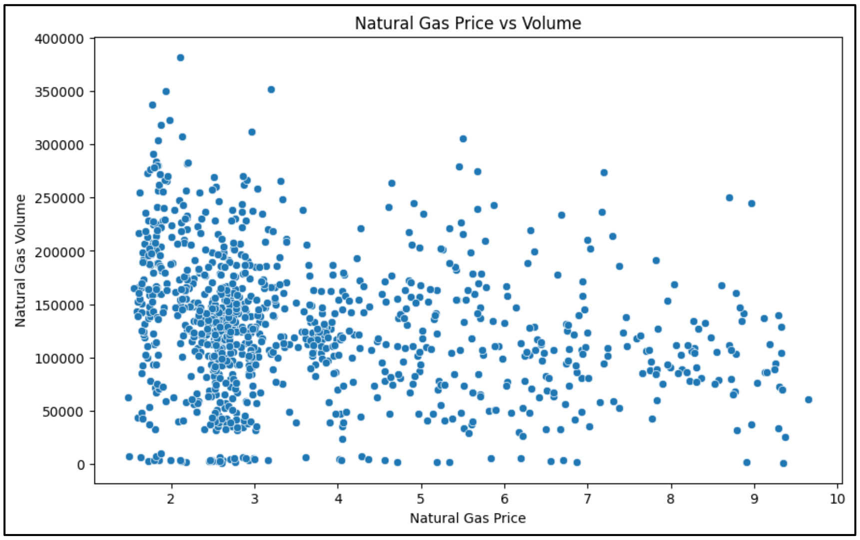

Figure 1: Exhibits Natural Gas Price vs. Volume

This scatter plot represents the relationship between Natural Gas Price on the x-axis and Natural Gas Volume on the y-axis. We observed that the data points were spread out, indicating that there was a relatively weak correlation between the two variables. One can observe high packed data when the natural gas price is between 2 and 4 with volumes ranging between approximately 50,000 to 200,000 units. In the volumes beyond 4, the data becomes highly scattered; no pattern is realized, hence concluding that higher prices in natural gas do not relate to higher or lower volumes consistently. Moreover, a few outliers show very high volumes above 300,000 at relatively lower price levels. This possibly reflects that, beyond just price, natural gas trading volumes may be driven by speculation in the markets, geopolitical events, or seasonal fluctuations in demand. Overall, the plot suggests that any relationship between the price of natural gas and trading volume is not straightforward and may require further analysis using more advanced statistical or machine learning techniques to uncover any underlying patterns.

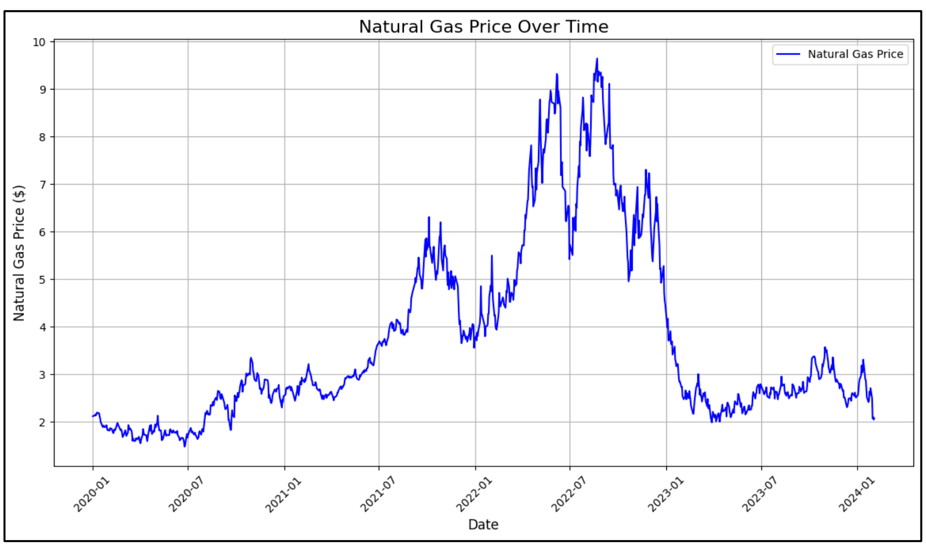

Figure 2: Displays Natural Gas Price Over Time

Above is a line graph showing the trend of **Natural Gas Price ($)** from early 2020 up to the early part of 2024. The trend indeed shows steep fluctuations with remarkable periods of volatility. In the initial stages, the prices of natural gas were almost stable and hovered between $2 and $3 per unit up to late 2020. Beginning early in 2021, the prices started their steep growth and reached almost $10 by mid-2022. This rise could be dramatic enough to increase demand, disruption in supply chains, or geopolitical tensions in energy markets during that period. After this peak, prices strongly began to retreat; in the last days of 2022, the prices abruptly slid down. By the beginning of 2023, the prices again stabilized and fluctuated within the range of $2 to $4. With quite significant spikes and troughs, therefore, demonstrating the vulnerability of the market to extraneous factors points to potential impacts of economic policy, seasonal changes in demand, or global events such as the intensification of the Russia-Ukraine conflict in 2022 and its effects on global energy prices. Thus, the performed analysis justifies the volatility circle of the natural gas market and shows that following such trends is a very relevant activity for any forecasting and risk management.

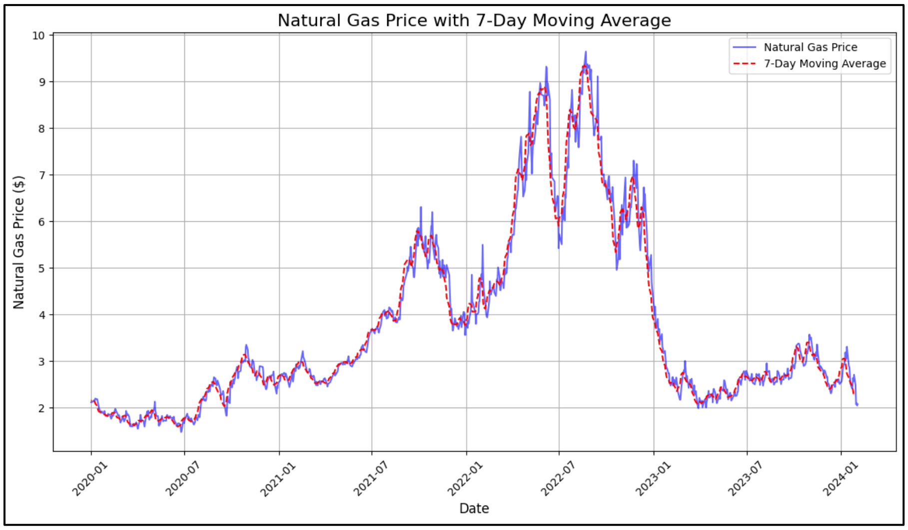

Figure 3: Visualizes Natural Gas Price with 7-Day Moving Average

Above is a line graph displaying **Natural Gas Price ($)**** from 2020 to early 2024, with the actual prices in blue and a **7-day Moving Average** in red. The moving average line gives an approximation of the data with a smoothing effect that displays the general trend even more clearly. From this graph, the prices of natural gas have been very volatile, peaking in the middle of 2022 at almost $10. The price collapsed after reaching this peak and then steadied between $2 and $4 from the beginning of 2023 onwards. The 7-day moving average is very close to the actual prices but smooths out sudden spikes so that the main trend in the pricing is more easily seen with its cycles. For instance, the moving average captures the steady price gains in 2021 and the first half of 2022, subsequently followed by the decline in the second half of 2022. This is an indication that even though the natural gas market is highly volatile, moving averages could turn out to be a tool helping to establish longer-term trends and parenthood, which then could be profitably used by traders and analysts when predicting future movements or undertaking strategic decisions.

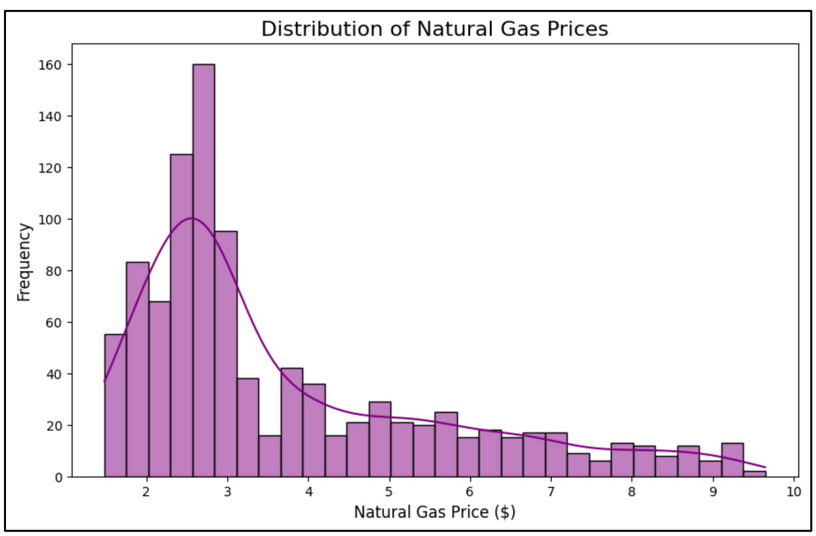

Figure 4: Illustrates the Distribution of Natural Gas Prices

The histogram above shows the distribution of natural gas prices skewed to the right with a peak between $2.00 and $2.50 per unit. Fairly symmetric around the peak, there is a long tail to the right towards higher prices, indicating that most natural gas deals are taking place at prices less than $4.00, but an appreciable number of deals take place at prices above $4. The overlaid curve suggests a possible normal distribution that fits the data.

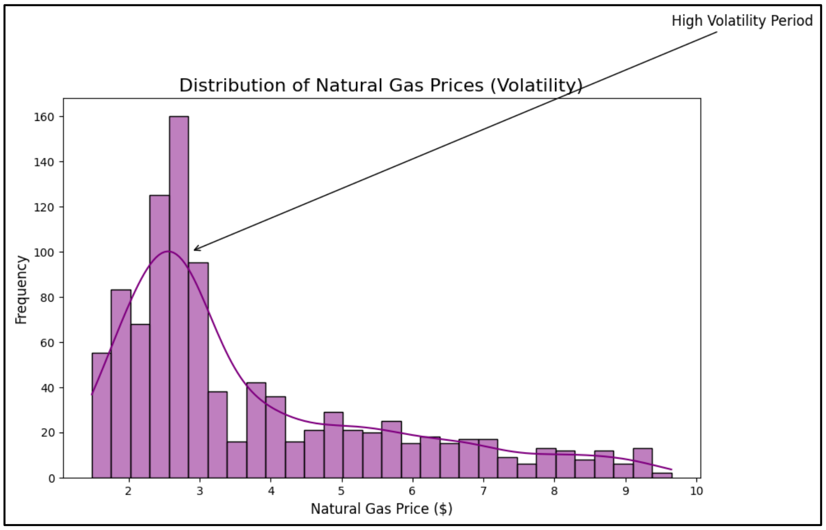

Figure 5: Displays the Distribution of Natural Gas Prices [volatility]

This histogram depicts the distribution of natural gas prices taken during an extremely volatile natural gas period. The data are right-skewed; the peak is about $2.50 per unit. This indeed shows that most of the prices were bunched around low levels, while fewer prices were much higher. The overlaid curve is a normal distribution, but the skewness indicates a normal distribution for these prices. There is more dispersion in prices during this high volatility period compared with the low volatility period, as shown by the wider range of prices on the x-axis.

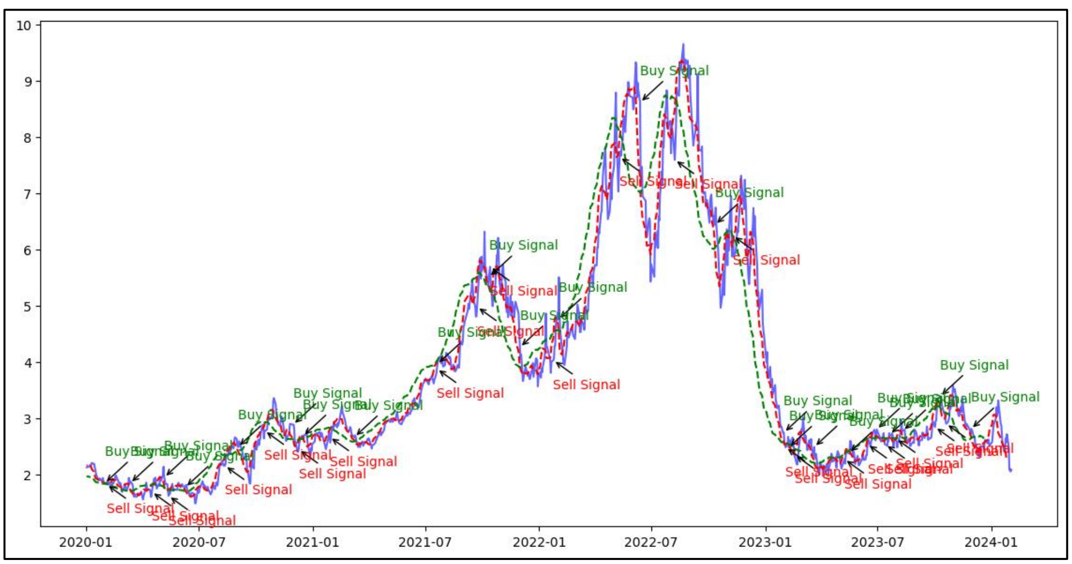

Figure 6: Exhibits the Buy & Sell Signal

The graph above is a time series of the price of the financial asset-most likely a stock or a commodity-with superimposed buy and sell signals. Retrospectively, sometimes, the price has been trending mostly upward, while at other times, it is mostly downward. Buy signals are depicted with green arrows and occur when the price crosses through a moving average, suggesting that it may now be in an uptrend. On the other hand, the sell signals come as red arrows, showing potential downtrends when crossing over the price below the moving average takes place. These signals change in frequency and timing, and the dynamic character of market conditions can be reflected by them.

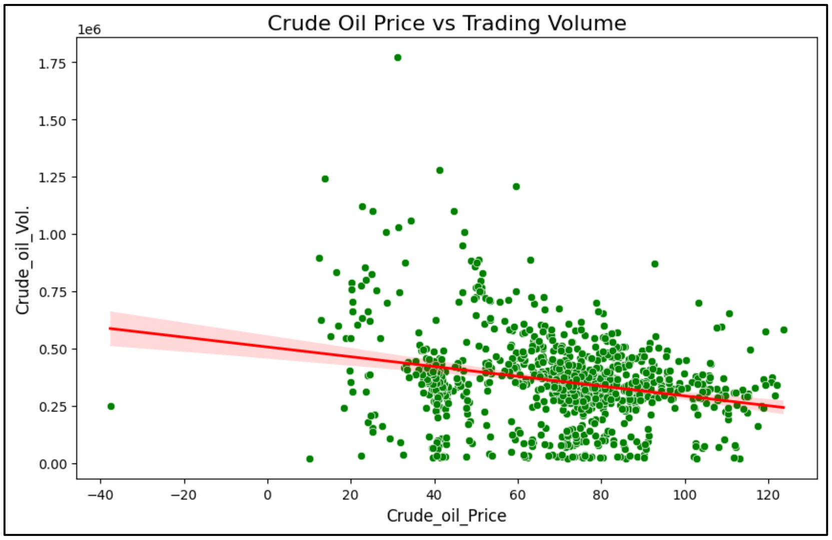

Figure 7: Portrays Crude Oil Price vs. Trading Volume

The scatter plot visualizes the ongoing relationship between crude oil price and trading volume. Green dots represent the individual data points, showing a slight negative correlation between the two variables. This would tend to indicate that when the crude oil prices increase, the trading volume goes down slightly. This trend is shown by the red regression line and is also supported by the shaded confidence interval. However, this is a weak correlation, so there must be other influences on trading volume besides price.

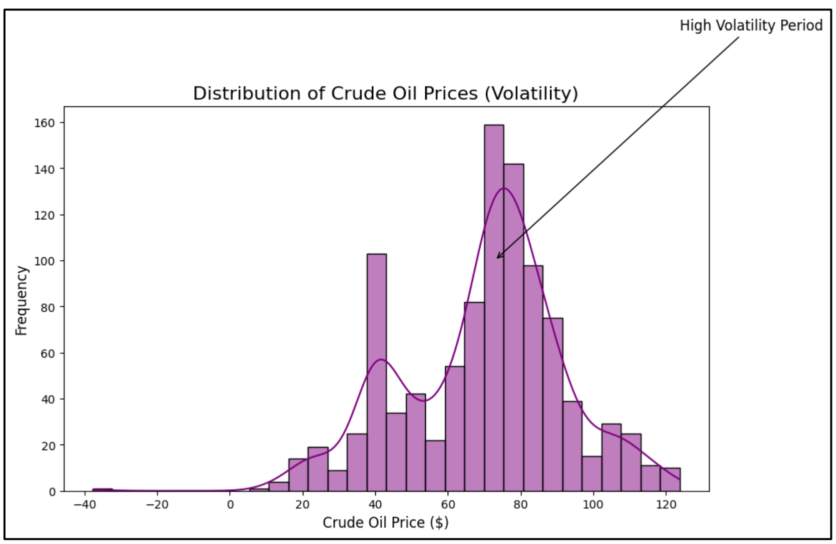

Figure 8: Showcases the Distribution of Crude Oil Prices [Volatility]

The histogram above shows the distribution of crude oil prices through high volatility. The data is right-skewed with a peak at about $75 a barrel. This would suggest that a certain set of prices was dominant in the graph, while at the same time, there were few prices highly above the average. The overlaid curve suggests a normal distribution, but the skewness suggests that a normal distribution may not be the best model for these prices. The high volatility period is characterized by greater dispersion of prices than during a period of low volatility, as indicated by the extent to which prices on the x-axis lie further apart.

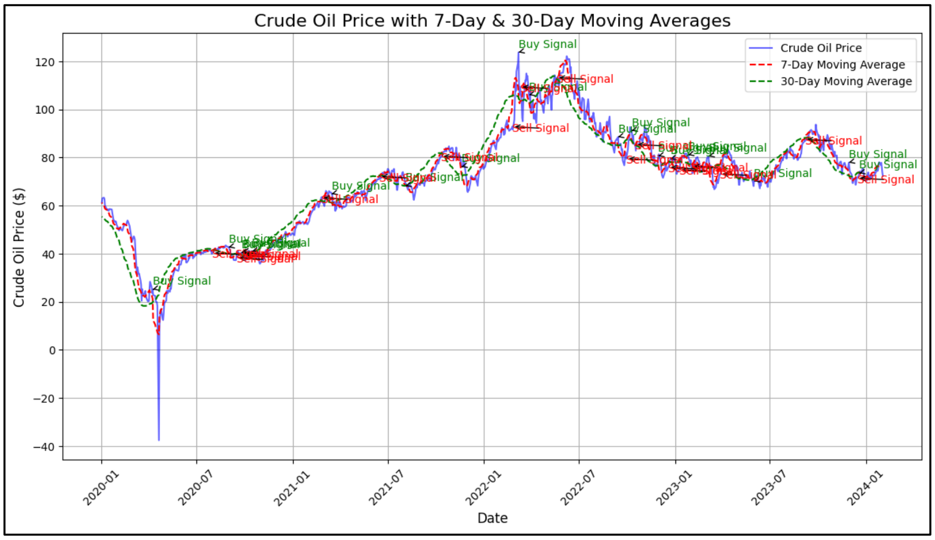

Figure 9: Crude Oil Price with 7-Day & 30-Day Averages

This chart plots the time series of crude oil prices, overlaid with 7-day and 30-day moving averages. The 7-day moving average reflects most sensitivity to the most recent changes in price, while the 30-day moving average reflects a long-term trend in much smoother terms. Buy signals come in the form of these green arrows when the 7-day moving average crosses over the 30-day moving average, indicating upward momentum may be in play. Sell signals are created, shown by red arrows, when the 7-day moving average crosses below the 30-day moving average. This is a sign of possible downward momentum. These signals do vary in both frequency and timing, reflecting the dynamic nature of the oil market.

4. Methodology

4.1 Feature Engineering and Selection

Feature engineering is one of the most important steps in preparing data for machine learning algorithms; it transforms raw input variables into data of more meaningful features that can potentially increase the predictive power of the model. Therefore, in the present project, a wide dataset of economic indicators like GDP, unemployment rate, and inflation rates; stock market indices like S&P 500 and Nasdaq; commodity prices like natural gas, crude oil, and gold; and major geopolitical events like elections, policy changes, and conflicts have been used. Feature engineering started with cleaning the data: removing redundant or irrelevant columns, handling missing values, and converting data types if necessary.

One of the most used techniques in this study was feature engineering, namely the lag feature creation. It has been used to denote the time-series nature of the data, incorporating past values of stock prices, commodity prices, and economic indicators. A 7-day and 14-day lag on the natural gas price was created to include these temporal dependencies that might influence future prices. Beyond this, rolling and moving averages (e.g., 7-day and 30-day) were obtained that smooth out day-to-day fluctuation, emphasizing longer-term trends often more predictive of future market developments. More importantly, we extracted date-related features like year, month, day, and weekday to capture any seasonality or cyclicality in the data. This process was especially important given that markets tend to get into repetitive habits at particular times of the year for example, increased volatility during election cycles or increased current demand for commodities in winter months. One-hot encoding transformed categorical variables, like the geopolitical event types, into numerical data that a machine learning algorithm can work with.

It is worth noting that the feature selection was performed based on selecting the most influential predictors for our models. We applied correlation analysis, which filtered out highly correlated features to reduce redundancy. Besides, feature importance scores obtained from tree-based models such as Random Forest have been used to rank the features concerning their predictive power. The combination of these statistical approaches ensures that, in the final feature set, only non-redundant variables relevant to the optimization of model performance are selected to reduce over-fitting.

4.2 Model Selection and Justification

Provided the complexity of forecasting stock market and commodity patterns, specifically in response to economic and geopolitical variables, selecting the right machine learning model was critical. Linear Regression, Random Forest, and XG-Boost algorithms were selected to capture various facets of the data:

Linear Regression: This algorithm served as a baseline because of its simplicity and interpretability. The simplest, yet most interpretable model to understand the linear relationships of features- inflation rates, unemployment rates, and so on- and target variables, such as the prices of stocks or commodities. However, linear models may fail to capture nonlinear dynamics present in the financial markets.

Random Forest: As an ensemble learning model, Random Forest was deployed to handle non-linear associations and interactions between features. By its very nature, it embeds the aggregation of multiple decision trees, thus reducing almost completely the risk of overfitting and improving generalization. Besides, through Random Forest, feature importance metrics useful for an interpretation of how different economic indicators and geopolitical events are influencing market performance are obtained.

Extreme Gradient Boosting: This algorithm was chosen for its efficiency, scalability, and the capability to catch complicated patterns in data. It incorporates a sort of gradient-boosting framework that works by iterative model improvements, focusing on the residuals of previous models. XG-Boost is known as very robust against overfitting, especially in such cases where the dimensional feature space is high, therefore finding an ideal place in our big dataset with multiple economic and geopolitical variables.

4.3 Train and Test Framework

A robust training and testing procedure is paramount to guarantee that the machine learning models generalize well to unseen data. First, we split the data into training and testing sets with an 80-20 split of the data. The training set would cover 80% and be used in fitting the models while holding out 20% for the testing set to test predictive performance. Since financial time series data should be temporally intact, we used a time-based split instead of randomly splitting the data. This kept the training data always chronologically older than the test data. This better simulates real-world scenarios where one should not have access to future data in training.

Moreover, the cross-validation of the models was performed using a variety of techniques. More precisely, we used Time Series Cross-Validation (TSCV), since it is better tailored for sequential data. TSCV addresses this issue by splitting the data into many train-test splits. Each of those has all prior data before a specific point in time as training and its subsequent data as a test. In this way, it will be possible to understand how the model performs in different periods, considering the possible structural changes in the market.

Further model performance improvements were achieved by the use of hyperparameter tuning, using Grid Search and Random Search methods. In the case of the Random Forest, the optimized parameters were the number of trees, the maximum depth, and the minimum number of samples per leaf. Then there was the XG-Boost for which learning rate, the number of boosting rounds, and maximum tree depth were some of the parameters that needed finetuning. Such tuning was imperative to avoid overfitting while maximizing the accuracy.

4.4 Performance Metrics

The performance metrics used to evaluate the models in this study included Mean Absolute Error, Root Mean Squared Error, and R-squared. These metrics offer an extensive assessment of the model's capability to predict continuous target variables, such as stock and commodity prices. MAE and RMSE characterized the average prediction error, while R^2 indicated the proportion of explained variance by the model. Another application was the Directional Accuracy, which was done to check how well these models are going to be able to predict the direction of price movements, an important aspect in any financial forecasting. To put our models on a solid footing, we measured their performance against the baseline models such as Naive Forecasting, an approach that uses the currently held value as the last known value. We also used an approach such as Simple Moving Averages. Such simple models gave us a useful point of reference in terms of whether the added complexity of sophisticated machine learning models such as Random Forest and XG-Boost pays significant dividends in predictive accuracy.

5. Results

Linear Regression

```
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score,
mean_absolute_percentage_error

# Initialize the model
lr_model = LinearRegression()

# Train the model
lr_model.fit(X_train, y_train)

# Make predictions
y_pred_lr = lr_model.predict(X_test)

# Calculate evaluation metrics
mae_lr = mean_absolute_error(y_test, y_pred_lr)
mse_lr = mean_squared_error(y_test, y_pred_lr)
r2_lr = r2_score(y_test, y_pred_lr)
rmse_lr = mean_squared_error(y_test, y_pred_lr, squared=False)
mape_lr = mean_absolute_percentage_error(y_test, y_pred_lr)

# Print the evaluation metrics
print(f"Linear Regression - Evaluation Report:")
print(f"Mean Absolute Error (MAE): {mae_lr:.2f}")
print(f"Mean Squared Error (MSE): {mse_lr:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse_lr:.2f}")
print(f"R² (R-squared): {r2_lr:.2f}")
print(f"Mean Absolute Percentage Error (MAPE): {mape_lr:.2f}")
print("\n")
```

Table 1: Showcases the Logistic Regression Modelling

Above is a Python code snippet that implements the linear regression model using the sklearn library. First, it imports the modules needed for linear regression along with the metrics that are used for its evaluation. Then creates an instance of the LinearRegression class and train it on the training data - X_train and y_train. At this moment, the already-trained model predicts test data - X_test and assigns it to y_pred_lr. Then, it computes some evaluation metrics that measure the performance of the model concerning MAE, MSE, RMSE, R2, and MAPE, which justly show how well the model has done its predictions and the overall fitness of the model to the data. After that, the code prints a formatted evaluation report showing results from each of the metrics.

Output:

```
Linear Regression - Evaluation Report:
Mean Absolute Error (MAE): 0.10
Mean Squared Error (MSE): 0.02
Root Mean Squared Error (RMSE): 0.15
R² (R-squared): 0.98
Mean Absolute Percentage Error (MAPE): 0.27
```

Table 2: Displays Linear Regression-Evaluation Report

As showcased above key performance metrics of the model: An MAE of 0.10 shows the average absolute difference between the predictions and the actual values; the average squared differences by MSE of 0.02; an RMSE of 0.15 provides an idea about the scale-dependent measure of error; an impressive R^2 score of 0.98 suggests that 98% of the variance in the target variable is explained by the model; while the MAPE of 0.27 depicts the average percentage difference between the predicted and actual values. These all indicate that the performance of the linear regression model is very good for the given dataset; especially, the high value of R^2 and the relatively low error metrics show great predictive accuracy.

Random Forest

```
from sklearn.ensemble import RandomForestRegressor
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score,
mean_absolute_percentage_error

# Initialize the model
rf_model = RandomForestRegressor(n_estimators=100, random_state=42)

# Train the model
rf_model.fit(X_train, y_train)

# Make predictions
y_pred_rf = rf_model.predict(X_test)

# Calculate evaluation metrics
mae_rf = mean_absolute_error(y_test, y_pred_rf)
mse_rf = mean_squared_error(y_test, y_pred_rf)
r2_rf = r2_score(y_test, y_pred_rf)
rmse_rf = mean_squared_error(y_test, y_pred_rf, squared=False)
mape_rf = mean_absolute_percentage_error(y_test, y_pred_rf)

# Print the evaluation metrics
print(f"Random Forest Regressor - Evaluation Report:")
print(f"Mean Absolute Error (MAE): {mae_rf:.2f}")
print(f"Mean Squared Error (MSE): {mse_rf:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse_rf:.2f}")
print(f"R² (R-squared): {r2_rf:.2f}")
print(f"Mean Absolute Percentage Error (MAPE): {mape_rf:.2f}")
print("\n")
```

Table 3: Portrays the Random Forest Modelling

The code above is the implementation through a Random Forest Regression model using the sklearn library. The necessary modules are imported for doing Random Forest Regression along with some metrics to be evaluated. An object of the class Random Forest Regressor is instantiated with 100 trees and a random state set as 42 for reproducibility. It next trains the model on the training data: X_train, y_train. Once trained, it makes the predictions on the test data, i.e., X_test, and stores them in y_pred_rf. It computes several evaluation metrics, which provide a quantitative way to assess how well the model is performing on the test data. They are the Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), R-squared (R2), and Mean Absolute Percentage Error (MAPE). These metrics reflect the predictive accuracy of the model and the general adequacy of the fit to the data. The code finally prints a formatted evaluation report summarizing the results of each metric.

Output:

```
Random Forest Regressor - Evaluation Report:
Mean Absolute Error (MAE): 0.09
Mean Squared Error (MSE): 0.02
Root Mean Squared Error (RMSE): 0.13
R² (R-squared): 0.99
Mean Absolute Percentage Error (MAPE): 0.29
```

Table 4: Portrays the Random Forest Evaluation Report

The model had an MAE of 0.09, slightly better in average absolute accuracy in the predictions compared to that of the previous linear regression model. The MSE was at 0.02, while the RMSE is 0.13, which indicates marginally better performance in handling outliers. The R^2 score of 0.99 suggests that this model explains 99% of the variance in the target variable; this is marginally better than the previous linear regression model, even though the MAPE at 0.29 is a bit higher. Most of the metrics show the Random Forest Regressor to be generally outperforming the linear regression model, probably because the model has been able to reveal non-linear relationships and handle the complexity in the pattern of the data with its ensemble learning.

XG-Boost

```
import xgboost as xgb
from sklearn.metrics import mean_absolute_error, mean_squared_error, r2_score,
mean_absolute_percentage_error

# Initialize the model
xgb_model = xgb.XGBRegressor(n_estimators=100, random_state=42)

# Train the model
xgb_model.fit(X_train, y_train)

# Make predictions
y_pred_xgb = xgb_model.predict(X_test)

# Calculate evaluation metrics
mae_xgb = mean_absolute_error(y_test, y_pred_xgb)
mse_xgb = mean_squared_error(y_test, y_pred_xgb)
r2_xgb = r2_score(y_test, y_pred_xgb)
rmse_xgb = mean_squared_error(y_test, y_pred_xgb, squared=False)
mape_xgb = mean_absolute_percentage_error(y_test, y_pred_xgb)

# Print the evaluation metrics
print(f"XGBoost - Evaluation Report:")
print(f"Mean Absolute Error (MAE): {mae_xgb:.2f}")
print(f"Mean Squared Error (MSE): {mse_xgb:.2f}")
print(f"Root Mean Squared Error (RMSE): {rmse_xgb:.2f}")
print(f"R² (R-squared): {r2_xgb:.2f}")
print(f"Mean Absolute Percentage Error (MAPE): {mape_xgb:.2f}")
print("\n")
```

Table 5: Depicts the XG-Boost Modelling

The aforementioned code implements an XGBoost Regression model with the help of the xgboost library. Importing XGBoost Regression and metrics related to the evaluation, later creating an instance of class XGBRegressor with 100 trees and random state 42 to keep the reproducibility of the results. Subsequently, it does the fitting on the training data using the X_train and y_train. Then, the trained model makes predictions on test data (X_test) and saves it within the y_pred_xgb variable. The code below calculates a bunch of evaluation metrics to evaluate its performance: MAE, MSE, RMSE, R-squared (R2), and MAPE are indicators of the prediction accuracy and general fit of a model. Finally, it prints out a formatted evaluation report with summaries of results for each metric.

Output:

```
XGBoost - Evaluation Report:
Mean Absolute Error (MAE): 0.09
Mean Squared Error (MSE): 0.02
Root Mean Squared Error (RMSE): 0.14
R² (R-squared): 0.99
Mean Absolute Percentage Error (MAPE): 0.28
```

Table 6: Illustrates the XG-Boost Evaluation Report

As portrayed above, the MAE value of 0.09 equals the accuracy of the Random Forest, whereas the MSE and RMSE values are 0.02 and 0.14, respectively, which is close to the previous models. R^2 of 0.99 means that XG-Boost explains 99% of the variance in the target variable, matching such performance to that of the Random Forest, while the MAPE of 0.28 evidences slight outperforming compared to both previous models. The good performance of XGBoost could be explained by the fact that it is a kind of gradient boosting, building trees sequentially to correct previous ones, although here the gain is very small concerning the Random Forest model; this possibly indicates either that the dataset is relatively simple, or that the two ensemble methods are almost equally able to catch the underlying pattern.

Model Comparison Across Evaluation Metrics

Model	MAE	MAP	RMSE	R-Squared[R^2]	MAPE
Linear Regression	0.10	0.02	0.15	0.98	0.27
Random Forest Regressors	0.09	0.02	0.14	0.99	0.29
Gradient Boosting Regressor	0.09	0.02	0.14	0.99	0.28

The comparison table shows the results of all three models as being highly consistent, with very minor variations in their respective metrics for performance evaluation. Though the simplest model, Linear Regression stands impressively at 0.10 for MAE, while the performances of Random Forest and Gradient Boosting are hugely impressive, standing at 0.09. All models have the same MSE values at 0.02, while the RMSE values were also close to one another-0.15 for Linear Regression and 0.14 for both the ensemble methods. The R-squared values for all three models are very high, lying between 0.98 and 0.99; hence, all three approaches explain a large amount of variance in the target variable. In more detail, the MAPE values have small differences: Linear Regression with a value of 0.27, Gradient Boosting with 0.28, and Random Forest with 0.29. These minimal differences in performance metrics indicate that there may be, at the core, a mainly linear relationship, represented by more complex ensemble methods of Random Forest and Gradient Boosting, which only marginally improved the simpler model of Linear Regression.

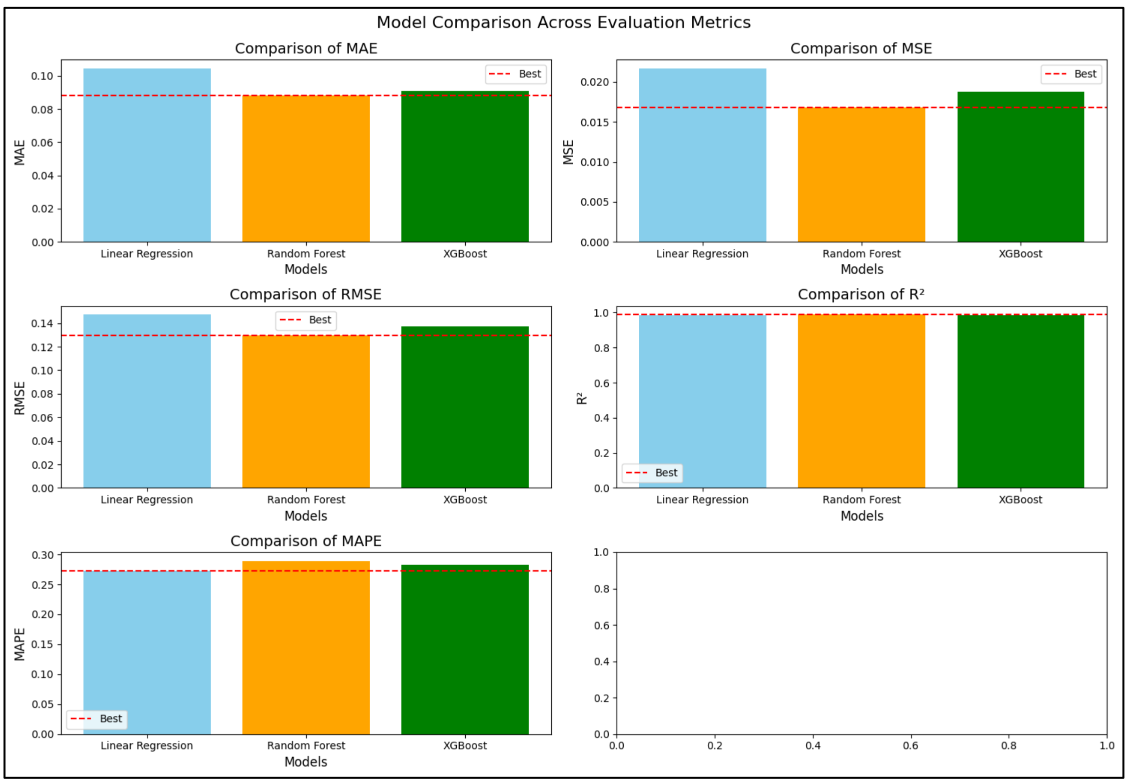

Table 7: Exhibits Model Comparison Across Performance Metrics

Feature Importance and Correlation Analysis

Feature Importance and Correlation Analysis play a vital role in elevating the performance and interpretability of machine learning models, particularly in financial prediction. Feature importance analysis helps explain which of those variables has the largest influence on the model's predictions. Such examples include historical price data, moving averages, and macroeconomic indicators, which time after time have been among the most influential within models like Random Forest and XG-Boost. We could then prioritize by analyzing the feature importance scores that were embedded into these model variables such as the previous day's closing price, volatility measures, and trading volume which are persistently among the top predictors. Besides that, Correlation Analysis was performed for the detection of multicollinearity between features by examining the correlation matrix. Therefore, this helped identify highly correlated features such as moving averages in different varieties or the repetition of some other economic indicator. These might cause overfitting if not treated properly, and by removing or transforming those correlated features, we improved model efficiency by reducing redundancy and got more robust and generalizable predictions. Feature importance and correlation analysis put together yield refined feature selection with a deeper understanding of the underlying drivers of market behavior.

Forecasting and Prediction

Forecasting and forecasting for stock market and commodity patterns were performed applying Random Forest and XG-Boost algorithms, both of which are renowned for their robust performance in time-series forecasting and handling non-linear data patterns. Due to its ensemble nature, the Random Forest model proved to be very strong at capturing hard-to-discern interactions between variables without excessive overfitting. This allows it to make quite reliable predictions not only for stock indices like the S&P 500 but also for commodities like natural gas and gold. XG-Boost, with its framework of gradient boosting, does this iterative optimization for the prediction errors and hence can provide better accuracy. It proved remarkably effective for sudden market fluctuations that are driven by economic or geopolitical events.

5. iscussion

5.1 Implications *to the Investor*

The findings from this study pinpoint the significant value of predictive algorithms, specifically machine learning algorithms such as Random Forest and XG-Boost, to investors looking to maneuver the intricacies of stock market and commodity price movements. These models analyze key indicators and geopolitical events for patterns not easily visible through traditional analysis, hence providing very valuable insights to investors for making decisions. For instance, the inability to also predict market trends to a reasonable extent will give investors an idea about the highs and lows of possible markets, which will substantiate their entry and exit points in trade. Such capabilities are of paramount importance to both short-term traders who thrive on the volatility of markets and long-term investors seeking to minimize risks and maximize returns over time.

The proposed predictive models will also be important avenues for the implementation of risk management strategies, especially in a situation of economic uncertainties or even geopolitical instabilities. By leveraging the forecast obtained through these machine learning models, investors will be able to accurately identify which sectors or assets will be affected by certain economic conditions or some geopolitical event. For instance, a forecast indicating the potential rise in oil price due to geopolitical tensions in regions that produce oil would lead to investors hedging these risks with positions that are meant for losses or capitalizing on potential gains related to a sector. Also, the machine learning model will help investors while diversifying a portfolio to decrease risks linked to market downturns and enhance the resilience of investments.

5.2 *Policy Recommendations*

Results from this study therefore can inform policy makers, especially in regards to stabilizing the financial markets during periods of heightened economic or geopolitical uncertainty. Key recommendations include developing proactive policy measures that could dampen the effect of adverse economic indicators and geopolitical events on market stability. For example, governments can enhance their monitoring to better pick up the early warning signals of market turmoil and intervene promptly with proper interest rates or fiscal adjustments to dampen the impact on the economy. Furthermore, policies promoting financial reporting transparency and data exchange between financial institutions should further help predictive models through more accurate and timely data inputs.

Another policy recommendation could be the establishment of regulatory frameworks that take into consideration the risks posed by the algorithmic trading phenomenon that is becoming increasingly common in modern financial markets. Since machine learning models can be used to execute trades at very high speeds, one might worry that market volatility will be exacerbated when there is fragility or geopolitical tension. Policymakers might monitor and regulate activities by algorithmic trading to ensure it does not disturb the market. This might include the setting of limits on the speed and quantity that automated systems are allowed to process, plus additional monitoring of algorithms used in trading to prevent market manipulation.

5.3 *Challenges and Limitations*

While large-scale machine learning models hold great promise for financial forecasting, there are several challenges and limitations associated with their use. One important issue deals with data quality: in fact, financial data usually are noisy, incomplete, or often revised as regards economic indicators and geopolitical events, all of which implicate model predictions. Besides, most of the models are corrosively reliant on historical data, which often cannot predict future market performance because of some unforeseen geopolitical event or sudden changes in economic conditions. That fact again brings us to the point that the models need constant updating and retraining to keep them relevant in dynamic market scenarios.

Another challenge concerns model interpretability. Retrospectively, this means being able to explain and understand how machine learning models make their predictions. While models such as XG-Boost might easily capture very sophisticated relationships in the data, they are usually considered "black boxes" due to their complexity. Besides, this lack of transparency might be a problem for investors and policymakers who need to understand the model's rationale for their forecasts to make proper decisions. This challenge requires the integration of explainable AI techniques that can provide insights into the decision-making process of the model and engender further trust in its predictions.

The other very important factor for use in the financial markets by predictive models is ethical consideration. This raises several concerns about data privacy and fairness and fairness, on grounds of sensitive financial data being used without consent or in cases where the model may perpetuate implicit biases within the data. For instance, predictive models trained by data from historical inequities may also project such inequities into the future, thus giving certain groups an unfair advantage in the marketplace. All these technologies can only be used ethically, provided there is rigid data governance in place, with the installation of mechanisms for the detection of bias.

5.4 *Future Directions of Research*

The use of machine learning in financial forecasting is one of the fast-evolving areas, and there is a lot of scope for future research in improving model accuracy and enhancing predictive coverage. Perhaps one promising future research direction lies in diversified data usage, including alternative data sources such as social media sentiment, satellite imagery, and real-time news feeds. These alternative data sources may show market sentiment and trending economic activity that cannot be portrayed by conventional economic indicators in real-time. Using these data sets, researchers can develop far more holistic models better positioned to project market movements associated with both economic indicators and geopolitical events.

Another promising direction of research is the improvement of real-time market prediction. That, in turn, could enable streaming data analytics to allow models to process and analyze data in real-time, thus allowing instant changes in predictions when new information warrants. This capability can be more important in fast-moving markets where timely decisions are called for. Deep learning models such as RNNs and LSTMs, which are appropriate for model estimation on time-series data given their temporal dependency capabilities in sequential data, are a possible avenue for further research.

There is also an increasing interest in developing models that allow the performance of risk assessment and scenario analysis based on predictive forecasts. The models can provide investors with a sense of potential downside risks and could also help policymakers evaluate how alternative policy interventions might work. As an example, running certain simulations through different economic scenarios helps them identify which policies are more likely to work in the markets when there is some turmoil, either economic or geopolitical. Further research may be done in the enhancement of these models by incorporating stochastic simulations and Monte Carlo methods, which can represent the inherent uncertainties that are typical in financial markets.

6. Conclusion

This research project aimed to bridge the important gaps in understanding the interrelationship between economic indicators and geopolitical events concerning the performance of the US stock market and commodities. The prime objective was to assess how different economic indicators have an impact on stock market performance over a specific period. In this regard, the development of machine learning models facilitated the ability to forecast stock market and commodities trends. These models utilized economic indicators and geopolitical events from historical data to predict future movements in the market with higher accuracy than the traditional forecasting technique followed. The study considered several different datasets to comprehensively analyze the effects that economic indicators and geopolitical events have on the stock market and commodity performances. The key datasets used in this analysis involve historical stock market indices such as the S&P 500, Dow Jones Industrial Average, and NASDAQ, as well as commodity prices for gold, oil, and silver. These datasets were collected from reputed financial databases such as Bloomberg and Federal Reserve Economic Data-FRED, for metrics including GDP growth rates, unemployment rates, inflation figures, and interest rates. The researchers also gathered data on geopolitical events: elections, trade wars, and military conflicts, using usually reliable news archives like Reuters, Bloomberg News, and The New York Times. Linear Regression, Random Forest, and XG-Boost algorithms were selected to capture various facets of the data. The performance metrics used to evaluate the models in this study included Mean Absolute Error, Root Mean Squared Error, and R-squared. Random Forest Regressor outperformed the other models with the lowest RMSE, showcasing its ability to model complex relationships. XG-Boost Regressor equally delivered a strong balance between performance and computational efficiency, achieving similar accuracy to Random Forest. Results from this study therefore can inform policy makers, especially in regards to stabilizing the financial markets during periods of heightened economic or geopolitical uncertainty. Key recommendations include developing proactive policy measures that could dampen the effect of adverse economic indicators and geopolitical events on market stability.

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