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| RESEARCH ARTICLE

Assessing the Effectiveness of Machine Learning Models in Predicting Stock Price Movements During Energy Crisis: Insights from Shell's Market Dynamics

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| ABSTRACT

The global energy crisis has presented an unprecedented degree of volatility and uncertainty in financial markets, specifically impacting the stock prices of energy sector organizations. Accurate forecasting of stock price patterns during such turbulent periods is essential for informed decision-making by investors, policymakers, and industry stakeholders. The main purpose of this study was to assess the effectiveness of different machine learning models in predicting stock price movements during an energy crisis. This research investigated the stock price fluctuations of Shell during the energy crisis, considering historical data and machine learning techniques to identify patterns and trends. The dataset for this study was sourced from accredited and credible sources providing a more detailed view of how the variation in stock prices of major energy firms was influenced by different energy crises that occurred during the period 2021-2024. The proposed three big energy companies listed under their abbreviations for convenience comprise ExxonMobil (XOM), Shelll-SHEL, and BP-BP; after which historical data was gathered using y-finance. This dataset was of great help to analysts interested in financial analysis, market behavior, and the impact of global events on the energy sector. The data consisted of the daily adjusted closing prices of the selected companies from January 2021 to date. Models like Logistic Regression, Random Forest classifiers, and Support Vector Machines classifiers were deployed since they offered distinct strengths and were capable of offering the right potential. The proven performance metric used encompassed Precision, Recall, Accuracy, and F1-Score. The Random Forest model has the highest accuracy at 0.52, followed by Logistic Regression with an accuracy of 0.51, and then the Support Vector Classifier with an accuracy of 0.50. There are great opportunities in the integration of machine learning and financial forecasting to improve predictive accuracy, especially in these volatile markets where prices fluctuate rapidly with immense uncertainty. Predictive models might also be put into practice by decision-makers within several finance-related spheres to great avail. In this regard, investment firms could practice machine learning for portfolio management by way of automated trading based on market signals in real-time. Predictive modeling of the energy crisis brings huge dividends for investors and analysts. The first among the main recommendations is to take advantage of the model predictions within a diversified investment strategy. In this direction, the investors must use the output of those different predictive models not as an isolated lead but as a complementary tool enhancing the traditional analysis techniques.

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| KEYWORDS

Stock Price Prediction, Energy Crisis, Shell, Energy Crisis, Market Volatility, Predictive Modeling, Financial Markets, Energy Sector

| ARTICLE INFORMATION

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Introduction

Background and Context

According to Hasan et al.(2024a), the energy crisis worldwide has struck financial markets since it has underlined the interdependency between disruption to energy supply and economic stability. Over the last decade, a combination of geopolitical, environmental, and economic factors has come together to create a very fragile global energy ecosystem. Events such as geopolitical conflicts, supply chain bottlenecks, and the transition toward renewable energy are factors that further raise uncertainties and lead to sharp volatility in energy prices. As Chowdhury et al. (2024), reported that these dynamics ripple through world markets and more often than not hit companies in the energy sector, like Shell, hard. This therefore makes such company stocks an effective barometer of the energy market performance mirror display of changes in supply and demand, and investors' sentiments.

In this regard, the accurate forecast of stock prices becomes an important tool for stakeholders in the financial and energy sectors. Investors are interested in reliable forecasting models that help them manage the risk of portfolio diversification; policymakers and industry leaders need predictive insight to develop strategies that will bring stability to markets and ensure energy security (Topuz, 2024). Traditional financial models, which often assume market equilibrium and rely on historical averages, struggle to capture the complexity of modern energy crises. While currently applied, ML models have emerged as promising alternatives capable of detecting patterns from large data sets and adapting to nonlinear relationships (Islam et al., 2024).

Problem Statement

Rahman et al. (2024), reported that predicting stock price movements during periods of volatility, such as those resulting from an energy crisis, is unique in several ways. Traditional econometric models fall short of representing the complexity and dynamism of energy markets, which are driven by a combination of influences that range from geopolitical events to technological breakthroughs. Moreover, high-frequency market data and interactions among global and local variables also demand models with great capability in terms of processing a lot of information in the shortest time. On one side, the use of machine learning models offers quite substantial advantages concerning overcoming these problems. However, this is a circumstance in which any hope that the efficacy might be well warranted is at the mercy of everything from data quality, to feature selection and model architecture. Reza et al. (2024), contended that the nature of most ML algorithms being "black-box" also contributes to problems with interpretability, which in turn diminishes their acceptance among financial professionals. In the case of Shell, one of the largest multinational energy companies, the stakes are very high. The stock price of the company depends on many variables interacting in a complex manner: crude oil prices, currency exchange rates, government policies, and macroeconomic indicators. Therefore, this calls for an urgent need to review the robustness and reliability of ML models in predicting changes in stock price during such volatile periods.

Research Objective

The main purpose of this study is to assess the effectiveness of different machine learning models in predicting stock price movements during an energy crisis. The research will be using Shell as a case study to evaluate the performance of different ML algorithms, including regression models, tree-based models, and neural networks, in capturing stock price dynamics. Identify the key features and variables driving stock price movements within the energy sector. Compare the performance of machine learning models to that of traditional financial forecasting approaches to determine strong and weak points.

Scope and Relevance

This research investigates the stock price fluctuations of Shell during the energy crisis, considering historical data and machine learning techniques to identify patterns and trends. Since Shell is a globally operating company with a wide portfolio, the case of Shell will be ideal to explore the complexities in energy market dynamics. The following points fall within the scope of this work: analysis of the historical data of the stock of Shell with a special emphasis on periods of turmoil related to energy crises; applying both supervised and unsupervised ML methods to model the movement in the stock price; and testing the performance of those models using MSE, R-squared, and directional accuracy.

II. Industry Context

Energy Crisis and Stock Market Volatility

Shil et al. (2024), posited that of all the crises that have haunted humanity, the energy crisis retains its top position on the list with growing prices and strained supplies in this century. With the geopolitical battle, including tensions in key oil-producing areas of the world and the worldwide shift toward decarbonization, energies are in disarray. This is giving way to a scary imbalance in supply and demand, driving energy prices to blow up. These are disruptions directly related to the financial performance of energy companies such as Shell, while stock prices may be closely linked to market perceptions of stability and profitability.

Market volatility, based on the energy crisis, significantly tests the investment strategies of the energy sector. The great and rapid fluctuation in the stock price reduces investor confidence and compels stakeholders to adopt more cautious or speculative approaches. Interconnectedness in world markets amplifies energy price shock ripples, affecting other general financial indices-investor sentiment among others (Shawon et al., 2024). The volatility ushers in the use of sophisticated forecasting tools which may define the trends and dampen risk factors. These are challenges that make the application of machine learning models imperative, considering their handling of complex datasets for pattern recognition and adaptation to changes in conditions (Sumon et al., 2024b).

Shell: A Major Player in the Energy Industry

Officially known as Shell plc, Shell is the single largest energy multinational corporation of its kind around the world. Initiated in the 20th century, the organization has developed an entity focused on the production and distribution of crude oil and its fuels (Sumsuzoha et al.,2024). With great years behind the company, business deals that show how committed they were to global change brought a series of renewable energy investment decisions for portfolio diversification in recent decades. Yet, despite these, Shell remains so entangled with the fossil fuel industry that it is very vulnerable to the effects of energy crises (Sumon et al., 2024a).

Hasan et al. (2024b). postulated that the performance of Shell's stock in times of energy instability is of vital importance to a wide array of stakeholders. For investors, the stock is indicative of the health of the energy sector, reflecting wider trends in supply, demand, and regulatory environments. Due to this, every energy crisis, automatically draws huge attention from any market analyst, as changes in oil prices, whether lower or higher, geopolitical events, etc., directly affect valuation. Correct prediction of trends in the share price of Shell not only gives indications regarding the performance of the company itself but also provides signals toward the right path for the whole energy sector (Zalik, 2020).

III. Literature Review

Traditional Ways of Stock Prediction

Shen & Shafik (2024), stated that the quest to predict stock prices has long been a pivotal aspect of financial analysis, leading to the development of various traditional stock prediction methods. Of these, the most common are fundamental analysis, technical analysis, and time series forecasting. Fundamental analysis deals with estimating the intrinsic value of a firm through an analysis of financial statements, industry conditions, and economic indicators. Investors using this approach try to identify whether the stock is overvalued or undervalued based on its fundamental health. In contrast, technical analysis focuses on historical price and volume data, using charts and indicators to identify patterns that could indicate future price movements. It assumes that all information is already reflected in stock prices, and historical trends can be indicative of future performance (Zhong & Enke, 2024).

Adekoya & Weyori (2020), argued that stock price forecasting has indeed been one of the critical areas in finance, and conventional methods have played a prime role. Traditional forecasting mainly depends on statistical models, such as linear regression, ARIMA, or GARCH. These methods rely on the history of stock prices and try to identify patterns or trends that could indicate future movements. Although these methods are effective under stable market conditions, during periods of high volatility in energy crises, for example, are seriously limited.

According to Cai et al. (2017), one of the primary disadvantages of traditional approaches is based on linear assumptions and historical averages. Financial markets are very susceptible to nonlinear interactions and discontinuous shocks, which cannot be predicted using historical trends, especially during periods of crisis. Zheng & Umair (2022), reported that these models cannot again integrate a wide array of variables such as macroeconomic indicators, geopolitical events, and sentiment of news in real-time. Thus, their predictive power decreases while considering high-dimensional dynamic systems such as energy markets.

Machine Learning in Financial Forecasting

In retrospect, the application of machine learning in financial forecasting has drawn tremendous attention over traditional methods because it has the potential to improve the accuracy of stock price prediction. Machine learning algorithms can learn from data and further improve over time, thus offering robust solutions to the inherent complexities in financial markets. Regression trees, neural networks, support vector machines, and ensemble methods are some of the techniques that have been increasingly used to analyze large datasets including historical prices, trading volumes, and even alternative data sources such as social media sentiment and economic indicators (Chowdhury et al., 2024). The capability of machine learning models to capture nonlinear relationships and interactions among variables makes them particularly advantageous in volatile market conditions. These range from deep learning models with an immense number of layers of neurons, which could automatically extract features and patterns from raw data to make more granular predictions than could perhaps traditional methods (Islam et al. 2024).

Mohsin (2023) articulated that Machine learning has brought a new trend in financial forecasting, increasing the possibility of understanding and predicting stock price movements. This is because the design of these machine learning algorithms allows them to process large datasets and uncover any hidden patterns in ways that may not be revealed through linear analyses. Techniques applied include support vector machines, random forests, and neural networks, which are now widely popular in financial forecast studies. The strong points in machine learning models are the capability to quickly adapt to changing market conditions and to encompass diverse data sources. Techniques in NPL, for example, can comprehend news articles, social media posts, and earnings reports as an indicator of general market sentiment to create a prediction regarding stock price changes (Strauss & Trilling, 2018). Equally, deep learning models enable time-series data to be analyzed with improved precision by properly capturing nonlinear relationships and the interactions between various variables. Machine learning models show far greater predictive accuracy and robustness when compared to traditional methods in turbulent markets. However, they too have their challenges. Most of the algorithms in machine learning are black-box, and hence, tough to interpret their output; this may make financial professionals skeptical of adopting them. Furthermore, the quality and relevance of input data will be critical in determining the effectiveness of these models (Nguyen & Diab, 2023).

Related Studies

A significant volume of of research has been dedicated to stock price forecasting specifically within the energy sector, reflecting the unique challenges and characteristics of this industry. Many factors drive the energy sector, such as global oil prices, changes in regulations, and technological changes, making it a rich area for predictive analytics (Reza et al., 2024). These bear out in various studies, which have tried to predict stock trends in energy firms using both traditional and machine learning approaches with varying degrees of success. Several studies have used the fundamental analysis aspects to study how macroeconomic indicators impact the energy stocks' performances, while others applied some technical analysis that could find those patterns unique but peculiar to this sector (Islam et al., 2024).

Several studies have been done concerning the utilization of machine learning for stock price prediction, especially in the energy sector. Several such studies have depicted that the ML models are credible in unraveling complex dynamics of the market, hence giving agents good insight to inform their investment decisions (Hasan et al., 2024). For instance, the studies that have looked at the prediction of crude oil prices show that machine learning methods outperform traditional econometric models both in accuracy and strong responsiveness to market shocks.

According to Sumon et al., (2024), despite these developments, there are some serious gaps in the literature. Very few works have focused on the performance of ML models during an energy crisis period when market conditions are extremely volatile and uncertain. Further, only limited research has been conducted on applying machine learning to individual energy companies like Shell operating in highly dynamic and interconnected environments. Addressing these gaps is paramount to advancing the field and ensuring that ML models can adequately handle the singular difficulties of the energy sector (Shil et al., 2024).

IV. Data Collection and Preprocessing

Dataset Description

The dataset for this study was sourced from accredited and credible sources providing a more detailed view of how the variation in stock prices of major energy firms was influenced by different energy crises that occurred during the period 2021-2024. The proposed three big energy companies listed under their abbreviations for convenience comprise ExxonMobil (XOM), Shelll-SHEL, and BP-BP; after which historical data was gathered using yfinance. This dataset was of great help to analysts interested in financial analysis, market behavior, and the impact of global events on the energy sector (Topuz, 2024). The data consisted of the daily adjusted closing prices of the selected companies from January 2021 to date. This information was garnered for the comparison of various energy crises that came up and a comparative study of the wavering prices of oil and gas within the period 2021-2024. The above dataset provided full insight into investor behavior during times of uncertainty in supplies.

Preprocessing Steps

The Python code snippet demonstrated the different steps of data preprocessing on a stock price prediction task. It started with importing necessary libraries: pandas for data manipulation, NumPy for numerical operations, and sci-kit-learn for machine learning algorithms along with preprocessing tools. Next, the code loaded the stock data into a Pandas Data Frame, checked for missing values, and handled them by dropping the rows-imputation could be used instead. Feature engineering was done by creating new columns for daily price change, percent price change, and moving averages. A binary classification target was determined by the upward or downward movement of the price on the next day. Lastly, the data was divided into a training set and a test set; feature scaling is done via Min-Max-Scaler for the normalization of data to train models.

Exploratory Data Analysis (EDA)

Exploratory Data Analysis is the most important part of the entire research process and encompasses examining and visualizing data with a view of summarizing major characteristics of the data. This analysis uses statistical graphics and other data visualization methods. The central role of EDA involves uncovering patterns, anomaly spotting, hypothesis testing, and checking assumptions, thus guiding further insights toward analysis and decision-making. EDA, by understanding the structure and relationships in data, allows the researcher to detect trends and correlations that may guide him/her in choosing appropriate statistical models and improve the quality of results. Fundamentally, EDA forms a basis that gives more robustness and credibility to further analyses so that researchers may make informed interpretations grounded on a thorough knowledge of the underlying data.

Closing prices with Moving Averages

The Python code calculated and plotted the moving average of given stock data: The code first calculated the 50-day and 200-day moving average of the closing prices by calling the rolling () method with window sizes 50 and 200 accordingly. It then created a figure and plotted the closing prices, 50-day moving average, and 200-day moving average on the same plot using different colors and line styles for better visualization. Finally, it added labels, titles, gridlines, and a legend to the plot for better readability and understanding. It is often used in technical analysis to establish any trend and potential trading signals when the relationship between a security's closing price and its moving averages is concerned.

Output:

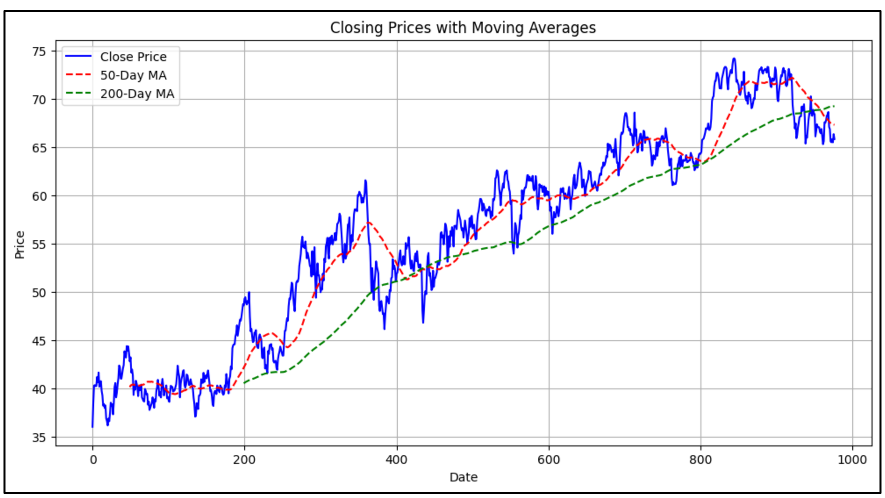

Figure 1: Portrays Closing Prices with Moving Averages

This graph depicts the closing prices of a stock over 1000 days, along with the 50-day and 200-day moving averages. The stock price is quite volatile, ranging from about 35 to 75. The 50-day moving average is in red and responds quicker to short-term changes in price, while in green is the longer-term trend of the 200-day moving average. It tends to be upwards over the entire period but with periods of consolidation and some downward movements. Trading signals can also be generated by the relationship of the stock price and the MA, for example: when the 50-day MA crosses above the 200-day MA-a bullish indicates one should buy the security, and when the 50-day MA crosses below the 200-day MA - a bearish signal - means one should sell the security.

Relative Strength Index (RSI)

The Python code computed and plotted the RSI for given stock data. The RSI is a momentum oscillator that measures the magnitude of recent price changes to evaluate overbought or oversold conditions. The code first calculated the price changes and then separated them into gains and losses. It then calculated the average gain and average loss over a 14-period window. The RS is the average gain divided by the average loss. Finally, the RSI is 100 - (100 / (1 + RS)). It then plotted the RSI versus time with horizontal lines at 70 and 30 to consider the overbought and oversold conditions, respectively.

Output:

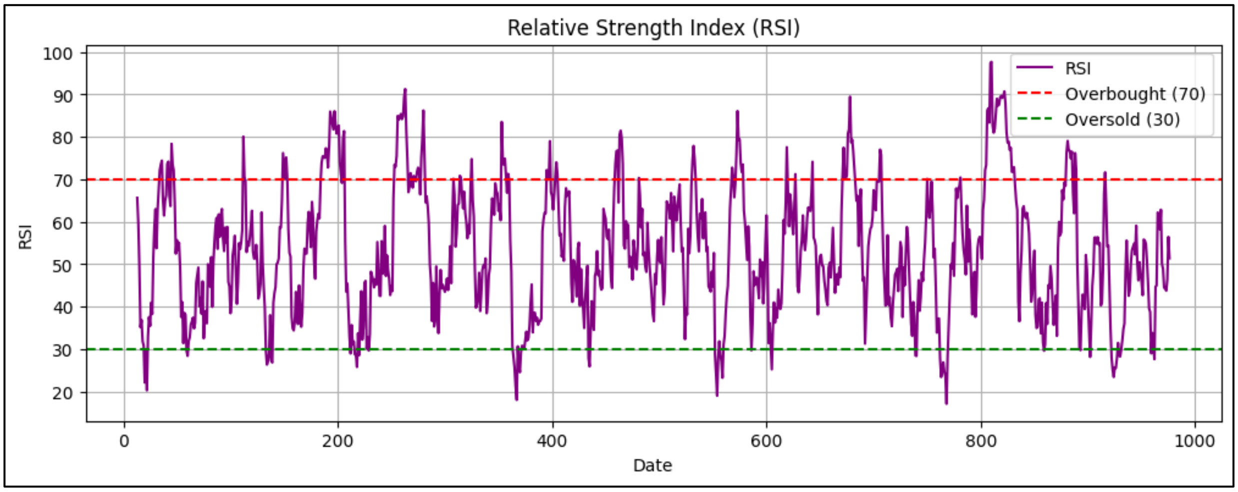

Figure 2: Illustrates Relative Strength Index (RSI)

The graph above shows the RSI for a stock over 1000 days. The RSI is a momentum oscillator that measures the magnitude of recent price changes to determine overbought or oversold conditions. The RSI fluctuates between 0 and 100, 2 with readings above 70 generally considered overbought and readings below 30 considered oversold. From the graph, it is observed that RSI was so volatile throughout the period that it broke through the overbought and oversold thresholds a couple of times. This would imply that the stock has moments of upward and downward momentum. A trader may take this information to their advantage when attempting to define their entry and exit points, for instance: selling after RSI had moved into an overbought level and buying it when RSI is at an oversold position. But worth noting is that the RSI is one indicator, and it should be used in conjunction with other technical analysis tools if the trader wants to have a fuller view of the trend in the price of the stock.

Moving Average Convergence Divergence (MACD)

The code in Python calculated and plotted the Moving Average Convergence Divergence for given stock data. MACD was a trend-following momentum indicator, which described a relationship between two moving averages of the price. To calculate the MACD, first, the difference between 26-day EMA and 12-day EMA yielded the MACD line. The signal line was calculated as the 9-day EMA of the MACD line. The difference between the MACD line and the signal line formed the histogram. Finally, it plotted the MACD line, signal line, and histogram against time:

Output:

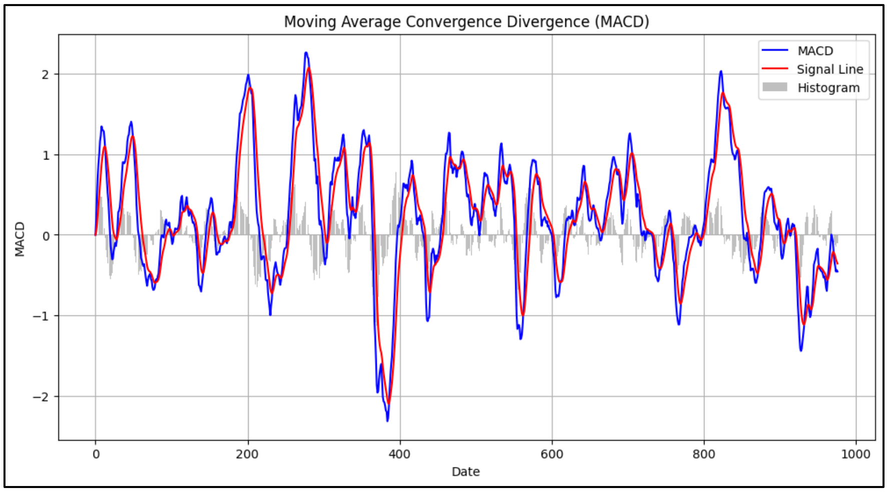

Figure 3:Displays Moving Average Convergence Divergence (MACD)

The given chart draws the MACD indicator of stock on the left side for 1,000 days. The MACD is a trend-following momentum indicator that illustrates the relationship between two moving averages of prices. The blue line in this chart is drawn by the MACD line; the red one, by the signal line, and the grey bars are given by the histogram. These oscillations of the MACD and signal lines around zero show that the stock price has seen both upward and downward momentum. The histogram plots the difference between MACD and signal lines. The positive values reflect plus differences, which means upward momentum, while negative values reflect minus differences, reflecting downward momentum. Also, notice how the MACD and signal lines cross each other a couple of times to provide buy and sell signals. The MACD line crossing over the signal line can be viewed as a bullish crossover-for instance, implying an uptrend-whereas whenever the MACD line crosses below the signal line, that can be a bearish crossover, which could mean a downward trend. This will provide traders with an approximation of possible entry and exit points. However, the MACD should not be used in isolation; it should be used in conjunction with other technical analysis tools to gain a better understanding of the price trend of the stock.

Bollinger Bands

The Python code executed and plotted the Bollinger Bands for a given stock data. The Bollinger Bands are volatility bands placed above and below a simple moving average of the closing price. First, the code computed the 20-day moving average and standard deviation of the closing price. Then, it calculated the upper and lower Bollinger Bands by adding and subtracting two standard deviations from the moving average, respectively. Finally, it plotted the closing price, moving average, and upper and lower Bollinger Bands on the same graph while it filled the space between these bands with shading as exhibited below:

Output:

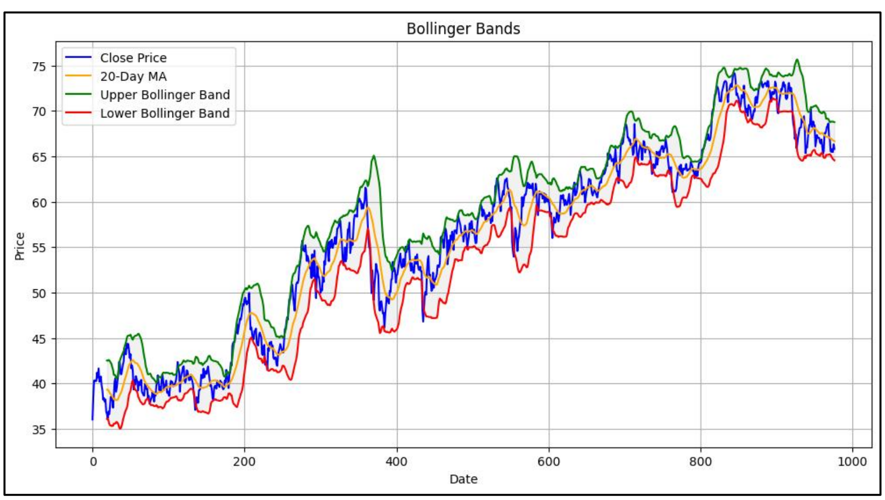

Figure 4: Showcases Bollinger Bands.

The chart plots the closing price for a stock over 1000 days, together with its 20-day moving average and its Bollinger Bands. The Bollinger Bands are volatility bands positioned two standard deviations above and below the moving average. This chart indicates that this stock has had some high points of volatility along with times when volatility is low during the period in consideration. These results show both the higher and lower Bollinger Bands, which the stock price has touched several times. This has caused both the overbought and oversold conditions to persist on this stock in various instances. This stock is not constant in volatility; therefore, it has expanded and contracted Bollinger Bands over time. It enables traders to gauge the areas of potential entry and exit points-for instance, buying when the price is at or near the lower band and selling when the price is at or near the upper band. In practice, though, one must be cautious not to trade using the Bollinger Bands alone but should consider incorporating other techniques of technical analysis to better understand the tendency of variation within the price of a given stock.

The Python script above started with the importation of libraries for time series visualization/analysis. Particularly, it imported mat plotlib. pyplot for the plot, seaborn giving an improved plotted functionality, and modules from pandas. Plotting for the lag plot and autocorrelation plot of the data stock. Afterward, it imported plot_acf and plot_pacf from tsaplots after importing statsmodel. Graphics to be able to access autocorrelated and partial AC plots. It then moved ahead to developing a figure and plotting the moving closing prices regarding time. This visualization allowed for a visual inspection of the price trends and patterns of the stock, which was further analyzed using the imported functions for autocorrelation and partial autocorrelation.

Output:

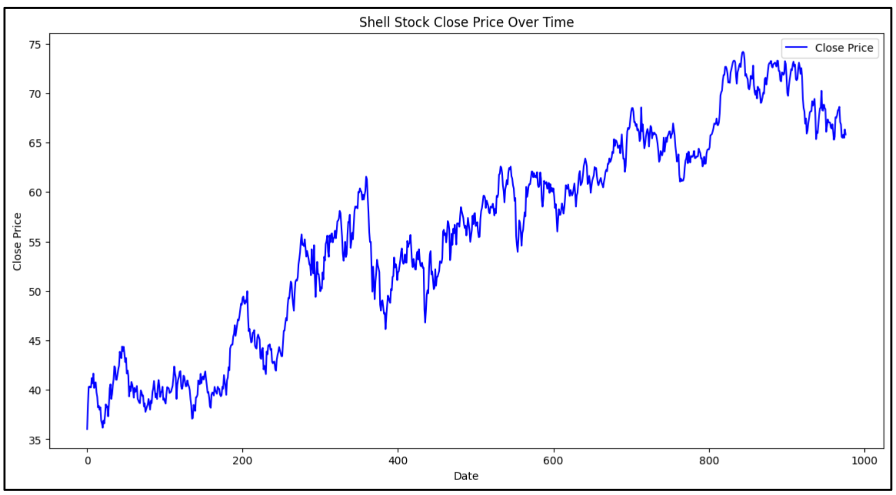

Figure 5: Visualizes Shell Stock Price Over Time

This chart displays the closing prices of the Shell stock over 1000 days. The volatility of the stock is quite high and moving within a wide range, from around 35 up to 75. The general tendency of the stock price is upward, although periods of consolidation exist along with some downward movements. Thus, this chart can be said to indicate that there have been phases of upward and downward strong momentum in the stock price movement of Shell. The information can allow the traders to identify some entry and exit points; however, one should just use this information in conjunction with other technical analysis tools for an in-depth analysis of the trend in the price of the stock.

Depicts Distribution of Close Prices

The Python code snippet was designed to generate a histogram depicting the closing price distribution for any given stock. It first imported necessary libraries, matplotlib.pyplot to plot and seaborn for enhanced plotting, then sets the figure size and created a histogram using sns.histplot, enabling kde to get a smoother view of the closing price distribution. This code sets the number of bins to 50 and colors the histogram purple. Then, it labeled the title, x-label as Close Price, and y-label as Frequency for better readability and displayed the plot.

Figure 6: Depicts Distribution of Close Prices

This graph shows the distribution of the closing prices. It shows some critical statistics of this data set: the purple colored histogram bars present the frequency of closing price, while the purple line overlaid presents a smoothed kernel density estimate of the general shape of the distribution. Notice that the closing prices mostly fall between 35 and 75, with fat peaks at 40 and 60, for example, as depicted by the high frequency of this range. Another big cluster may occur around 50; hence, there could be an important price zone around this value. Besides, there are remarkable gaps in frequency on some price intervals, which may indicate possible anomalies or less activity within those ranges. Overall, this distribution is somewhat bimodal, suggesting complexity in the market behavior reflected in the closing price.

This Python code visualized the trend in the everyday returns of a particular stock. First, it calculated day-over-day, taking the pct_change of the closing values. Then it figured out the figure size and formed a histogram of returns through 50 bins colored purple. Then, it sets the title, x-label as 'Daily Return', and y-label for better readability and plotted the figure. This analysis gave an idea of the range of daily returns, the frequency, and the overall shape of the distribution, which helped draw an idea about the risk and volatility of the stock.

Output:

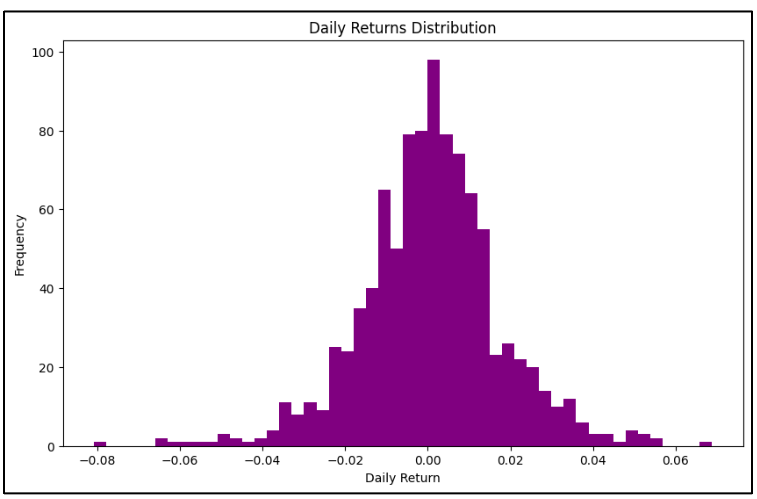

Figure 7: Daily Returns Distribution

This graph is a kernel density estimation of the distribution of the daily returns. The histogram here below indicates several interesting pieces of information on how that asset has performed over time. The x-axis represents the daily return, ranging approximately from -0.08 to 0.06, while the y-axis gives the frequency with which those returns come in. The described distribution is somewhat normal with a drastic peak at zero, indicating that most of the daily returns cluster around no change, which is typical for financial assets. Stability in their daily performances corresponds to the returns around zero; in turn, the tail of the distribution extends further toward both negative and positive returns, though with fewer occurrences, suggesting the infrequency of extreme returns. This histogram is also a bit negatively skewed, as may be noticed from the longer tail to the left of the graph. This outcome points out that while positive returns do come, they are fewer and usually smaller in magnitude than the negative ones. This distribution, in general, underlines the volatility and risk of this asset; therefore, there is a need for risk management in investment strategies.

Trading Volume Over Time

The Python code script generated a bar plot to visualize the trading volume of a stock over time. It first creates a figure of size 15*5; then, plt.bar() is used to plot the volume data versus the date index. The bars are colored in gray with an alpha value of 0.6 to show some transparency. Finally, it provides a title- "Trading Volume Over Time", labels the x-axis with "Date" and the y-axis with "Volume", and shows the plot. This plot will allow one to visually observe how trading volume has changed over this period, which will help identify periods of high and low trading activity.

Output:

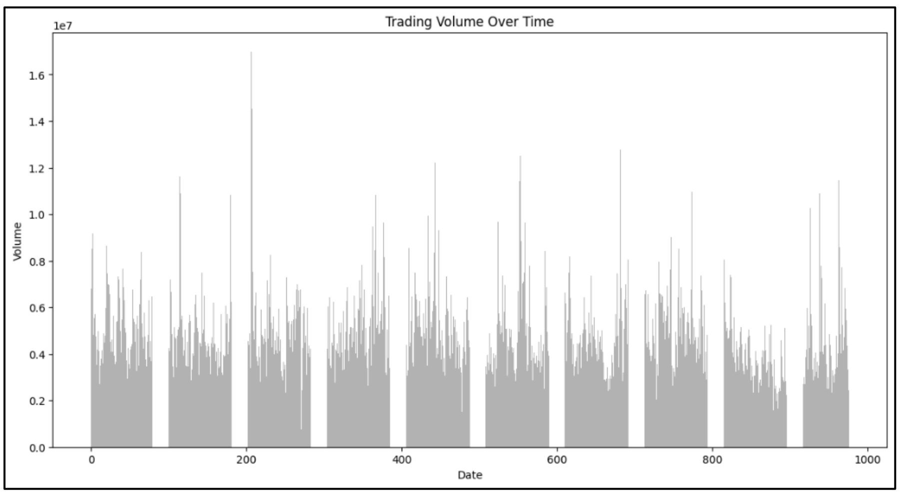

Figure 8: Trading Volume Over Time

The graph shows the trading volume over time. The x-axis is the timeline from 0 to 1000 days, while the y-axis shows trading volume in tens of millions. This set of data has a lot of ups and downs, especially on day 200 and day 800, with a volume of over 1.6 million, which just means that period was highly active. Generally consistent volume levels indicate a baseline of trading activity, while notable increases occur at regular intervals, possibly corresponding to market events or earnings announcements. Besides, the presence of lower volume periods interspersed throughout the timeline would imply phases of reduced trading interest or market inactivity. Overall, this distribution underlines the volatility and cyclical nature of trading volume, pointing to key junctures when investor interest reached its peak.

Feature Engineering

Feature engineering is one of the most important steps in any kind of stock price prediction; it enables one to identify and create relevant features that will improve the performance of a machine-learning model by a huge margin. In this context, features are variables used to explain the target variable, which, in this case, will be the stock prices. The main methodologies involve feature engineering using analysis of historical stock prices and volumes of trade. For example, the calculation of moving averages for 7 and 30 days may smooth out the price fluctuations and give a feeling about the probable trend. Besides, it is necessary to add other market variables that may impact stock performance, such as interest rates, inflation rates, and economic indicators related to GDP growth. Moreover, energy price volatility can also be included as a feature, especially for sectors that are very sensitive to energy prices. Features can be created that capture the relationship between energy costs and stock movements by tracking historical energy prices, such as crude oil or natural gas, and their correlations with stock. This may include percentage changes in energy prices over fixed periods or lagged variables that account for delayed market reactions. Carefully crafting these features will enable the model to make use of a much more informative dataset, which will result in much more accurate predictions.

Model Selection

The selection of machine learning models is crucially important for obtaining the best possible stock price predictions, especially when dealing with a volatile market, generally characterized by wild fluctuations and many external influences. Models like Logistic Regression, Random Forest classifiers, and Support Vector Machines classifiers were deployed since they offered distinct strengths and were capable of offering the right potential. Although Logistic Regression is the simplest, it is capable of modeling binary outcomes effectively and can thus be used as an important strategy in predicting up and down movements in stock prices using historical data. Being a linear method, its performance is often compromised while trying to capture relationships from highly volatile datasets. Random Forest, being an ensemble-based classifier, shows greater generalization over nonlinear data by avoiding overfitting, as the model has learned from multiple decision trees with averages for various predictions. This model is especially helpful in volatile markets where noise masks the underlying pattern in the data. Similarly, Support Vector Machines are robust in high-dimensional spaces and can create complex decision boundaries, making them well-suited for capturing intricate relationships in stock price movements. These models justify their existence because they can work with different distributions of data and also adapt to changing market conditions and a wholesome framework for predictions in a landscape so filled with uncertainty.

Training and Testing Framework

An effective framework of training and testing is highly crucial to realistically assess the performances of the chosen models. The procedure deployed involved dividing the dataset into training and testing, usually in the ratio of 80/20 or 70/30. The model fits according to the training set, which enabled it to learn from historical data, whereas the test set provided an unbiased assessment of model performance on unseen data. This split helped to avoid overfitting, where a model might perform extremely well on the training data but poorly on new data. To further enhance the model's reliability, cross-validation techniques were employed. Cross-validation involved partitioning the training dataset into several subsets, or folds, and iteratively training the model on a subset while validating it on the remaining data. The process was repeated an immense number of times, which allowed every observation to be part of the training and validation set. Methods such as k-fold cross-validation had an edge over others because they provided maximum utilization of data and gave an efficient measure of the model performance at different subsets. By implementing these strategies, the framework ensured not only robust model performance but also fine-tunes the hyperparameters for optimal results.

Evaluation Metrics

Model performance evaluations for a model in deriving the movement of stock price effectively using various metrics are an important step in the validation of such a model. The proven performance metric used encompassed Precision, Recall, Accuracy, and F1-Score. Precision refers to the ratio of the true positive predictions against all positive predictions that the model will have made since this helps the model stay away from false positives. Recall, on the other hand, gives the percentage of true positives among the total number of actual positive cases, which measures how well the model detects relevant instances. Accuracy is the overall measure for the correctness of predictions made by the model; however, this may not be accurate on imbalanced datasets. Thus, the F1-score, being the harmonic mean of precision and recall, becomes highly relevant since it, therefore, can balance the trade-off between both metrics. It will, hence, allow going deeper into the model performance when the class distribution is skewed in volatile markets. Taken together, these metrics offer a wide framework for testing predictive accuracy, guiding iterative model design improvements, and feature selection in the enhancement of reliability in the stock price prediction effort.

VI. Results and Analysis

Model Performance

a) Support Vector Machine Classifier

The Python code snippet performed the implementation of a Support Vector Classifier (SVC) model for a machine-learning task. It first created an instance of the SVC model using SVC (). Then, it trained the model on the scaled training data using svc-model-fit (X_train_scaled, y-train). After training, the model was used to make predictions on the scaled test data using svc_model.predict(X-test-scaled). Finally, the accuracy of the model was evaluated using the accuracy score (y-test, svc-preds) and the classification report printed to provide a detailed assessment of the model's performance. This code showcased a basic example of how to train and evaluate an SVC model in Python, which can be used for various classification tasks in machine learning.

Output:

Table 1: Showcases Support Vector Classifier Report

Support Vector Classifier Report:				
	precision	recall	f1-score	support
0	0.33	0.01	0.03	75
1	0.50	0.97	0.66	77
accuracy			0.50	152
macro avg	0.42	0.49	0.34	152
weighted avg	0.42	0.50	0.35	152
Support Vector Classifier Accuracy: 0.50				

The table above shows the classification report of a Support Vector Classifier model, which includes precision, recall, F1-score, and support for each class, both 0 and 1. Its overall accuracy is 0.50, meaning it correctly predicts the class label in 50% of the cases. The Precision for class 0 is 0.33; this means 33% of the instances that were predicted to be class 0 are class 0. Recall for class 0 is 0.01, which signifies the fact that the model identifies only 1% of the actual instances of class 0 correctly. For class 0, the F1-score is 0.03, which is the harmonic mean of precision and recall. This class 0 support is 75, hence it has 75 instances in the test set. Precision for class 1 is 0.50, recall 0.97, F1-score 0.66 and support 77. The macro average and weighted average metrics give a quick view of the overall performance of the model for both classes.

b) Random Forest Classifier

The Python code script performed the implementation of a Random Forest Classifier model that will solve the machine learning task. It instantiated a Random Forest Classifier: Random-Forest-Classifier(random-state=42). Then, it fitted the model on scaled training data using the rf-model.fit (X-train_ scaled, y-train). Finally, the code used the trained model to make predictions on scaled test data with rf_model.predict (X-test-scaled). This model's performance was evaluated based on accuracy via accuracy score (y-test, rf_preds), printing a classification report for the overall assessment of performance. This simple code shows the training and evaluation of the model using a Random Forest Classifier in Python:

Output:

Table 2: Displays Random Forest Classifier

Random Forest Report:				
	precision	recall	f1-score	support
0	0.51	0.47	0.49	75
1	0.52	0.57	0.55	77
accuracy			0.52	152
macro avg	0.52	0.52	0.52	152
weighted avg	0.52	0.52	0.52	152
Random Forest Accuracy: 0.52				

The above table exhibits the classification report for a Random Forest Classifier model: The precision, recall, F1-score, and support for classes 0 and 1 have been displayed in this matrix. The overall accuracy for this model is 0.52, indicating it correctly predicted class labels in 52% of the cases. The precision for class 0 is 0.51, which means 51% of the predictions in class 0 are actually in class 0. The recall for class 0 is 0.47, which means that the model correctly classified 47% of the instances that have class 0 in reality. The F1-score for class 0 is 0.49; the harmonic mean of precision and recall is here. Support for class 0 is 75, which is to say that in the test set, there are 75 instances of class 0. Class 1 has a precision of 0.52, recall of 0.57, F1-score of 0.55, and support of 77. Finally, we can look at the overall performance in both classes using the metrics of macro average and weighted average.

c) Logistic Regression

The Python code snippet demonstrated the implementation of a Logistic Regression model for a machine-learning task. It first created an instance of the Logistic Regression model using logistic regression (). Then, it trained the model on the scaled training data using lr_model.fit(X-train-scaled, y-train). After training, the model was used to make predictions on the scaled test data using lr_model.predict(X-test-scaled). Finally, the code determined the accuracy of the model through the function accuracy score (y-test, lr_preds). Then, it printed a classification report to characterize the model performances.

Output:

Table 3: Displays Logistic Regression Report

Logistic Regression Report:				
	precision	recall	f1-score	support
0	1.00	0.01	0.03	75
1	0.51	1.00	0.68	77
accuracy			0.51	152
macro avg	0.75	0.51	0.35	152
weighted avg	0.75	0.51	0.36	152
Logistic Regression Accuracy: 0.51				

The table above presents the classification report of a Logistic Regression model. It shows the model's performance metrics, including precision, recall, F1-score, and support for each class (0 and 1). The overall accuracy of the model is 0.51, indicating that it correctly predicts the class label in 51% of the cases. The precision for class 0 is 1.00, meaning that 100% of the instances predicted as class 0 are class 0. The recall for class 0 is 0.01, meaning that the model correctly identifies only 1% of the actual class 0 instances. The F1-score for class 0 is 0.03, which is the harmonic mean of precision and recall. The support for class 0 is 75, indicating that there are 75 instances of class 0 in the test set. The metrics for class 1 are similar, with precision at 0.51, recall at 1.00, F1-score at 0.68, and support at 77. The macro average and weighted average metrics provide an overall assessment of the model's performance across both classes.

Comparison of all models

The code in Python was computed to visualize the performance of three classification models: Logistic Regression, Random Forest, and Support Vector Classifier, using a bar chart. The model names and their accuracies are defined in a list. It created a figure and plotted a bar chart using model names as x-axis labels and their accuracies as the height of the bars. The bars were colored blue, green, and orange, respectively. This in turn sets the labels for the x-axis and y-axis, puts a title for the plot, adjusts y-axis limits between 0 and 1, and adds text to each bar from the plot of its accuracy, showing two decimal places. This allowed the analyst to visually contrast the results that were realized by the application of the mentioned classification techniques.

Output:

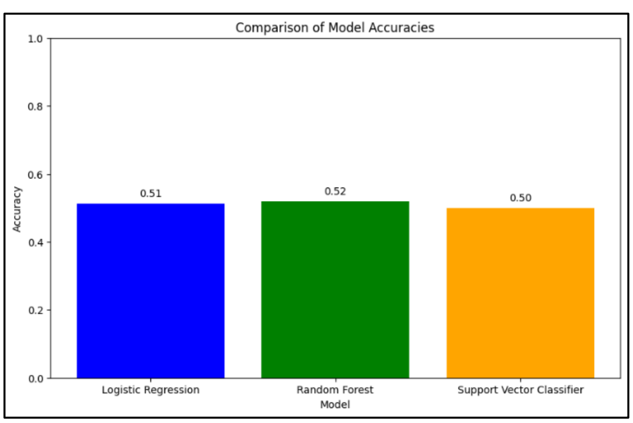

Figure 9: Comparison of Model Accuracies

The bar chart compares the accuracies of three classification models: Logistic Regression, Random Forest, and Support Vector Classifier. The Random Forest model has the highest accuracy at 0.52, followed by Logistic Regression with an accuracy of 0.51, and then the Support Vector Classifier with an accuracy of 0.50. This visualization gives a good comparison of model performances for the given dataset and probably indicates that the Random Forest model is perhaps the best choice to go with in this particular classification task.

Impact of the Energy Crisis on Forecasts

The energy crisis is characterized by the tremendous fluctuation in energy prices and disruption to supply chains. This factor will contribute to high market volatility, which influences the outputs of predictive models used to predict stock prices. During periods of heightened uncertainty-such as in the case of the energy crisis-the traditional models fail to capture the rapid changes in market dynamics. Externally, skyrocketing oil prices introduce volatility that can trigger radical changes in the investor psychology domain where prior historical relationships cannot be relied on. This element further muddles any predictions due to the implicit instability that results in higher levels of noise within the data itself, which leads to difficulty in the accurate forecast of stock movements. Models can also behave unpredictably because of the interplay of several exogenous variables, such as geopolitical conflict disrupting energy supply, changing consumer behavior, and shifts in demand for energy resources. Even relationships between the price of energy and the stock prices of related sectors will be more complex in crises. For instance, companies for which energy costs are a major expense, such as Shell, can almost immediately have operational cost effects that bias their stock performance. In such cases, models that are not constantly evolving in terms of these shifting relationships and volatility could generate forecasts significantly different from reality. This therefore emphasizes the importance of ongoing model refinement and feature engineering, which includes real-time market conditions.

Predictive Insights

The insights driven by predictive models during the energy crisis reveal a certain critical trend and pattern that may help an investor or manager make critical investment strategy and risk management decisions. First and foremost, the sensitivity of those particular stocks, especially in their energy component, to fluctuations in energy prices increases. For example, the forecasts of the stock price of Shell during the crisis showed that as the price of oil increases, the performance of stocks improves, reflecting how external economic factors influence investor sentiment and trading behavior directly. The models further stressed the importance of incorporating macroeconomic indicators-inflation rates, and consumer confidence indices into the predictive framework. Analysis of the model outputs demonstrated that, in periods when energy prices increased, volatility in Shell's stock and overall market increased, which reinforces the notion that investor behavior may be influenced by the general economic climate.

These models, while considering the stock price of Shell during the crisis, showed quite clear trends: initial drops in stock value were very often followed by recoveries that aligned with spikes in oil prices, suggesting that market participants were recalibrating their expectations based on real-time developments in the energy sector. For instance, in the first stages of the crisis, as energy prices fell due to decreased demand with the lockdowns globally, so did the stock price of Shell. As the energy markets began normalization and started a rally in price action, the Shell stock price started to rebound too, reflecting that investors were still behind the eight-ball on how this crisis would shake out for the fundamentals of the company longer-term. These predictive models further identified periods of overreaction, where panic selling or speculative buying had driven stock prices away from intrinsic valuations, thereby providing valuable insights to investors in identifying entry and exit points. In summary, predictive insights from this analysis underlined not only direct linkages of energy prices with Shell's stock but also outlined the need for adaptive strategies in trying to handle such complexity in volatile market conditions.

VII. Practical Applications

Implications for Investors and Analysts

From this perspective, predictive modeling of the energy crisis brings huge dividends for investors and analysts. The first among the main recommendations is to take advantage of the model predictions within a diversified investment strategy. In this direction, the investors must use the output of those different predictive models not as an isolated lead but rather as a complementary tool enhancing the traditional techniques of analysis. For instance, forecasts of stock prices can be combined with fundamental analysis, which incorporates the study of earnings reports, balance sheets, and cash flow statements of a company to make better investment decisions. In addition, investors should assume dynamic investment behavior during periods of high volatility, where the investor is agile and responsive to changing market conditions. Integrating real-time data feeds with model predictions will also help the investor in determining emerging trends and reversals of stock prices for gaining short-term opportunities by mitigating the risks.

Furthermore, risk management during periods of turbulence is multifaceted. Investors should put in place stop-loss orders to limit potential losses and consider options strategies, including hedging, where positions are taken in derivatives with the view of offsetting potential declines in stock values. Analysts can go further in refining risk management by undertaking scenario analysis: modeling the possible futures of the market under differing assumptions about future prices of energy and economic conditions. That would give more detail on how potential impacts could lead to stock movements and help be prepared against worst-case scenarios. Coupled with those strategies, model predictions will enable investors and analysts to take better positions given such a multifaceted energy market and hence prompt them to respond to rising opportunities and challenges.

Scalability to Other Energy Sector Companies

The developed methodology in this study is related to stock movement prediction during an energy crisis and cannot be confined to only one company but can also be extended to other firms operating within the energy industry. Notice how one of the strong points of this predictive approach is its flexibility: the principles driving feature engineering, model selection, and evaluation metrics are easily extended to various companies operating in different segments of the energy market, such as renewable energy firms, utility companies, and even ancillary service providers. Companies like NextEra Energy or Duke Energy would also benefit from similar predictive modeling, considering the peculiarities of market dynamics related to their operation.

Scaling this methodology requires customizing features and models to meet the unique characteristics of each company and their respective market segments. It would include the identification of relevant variables that are likely to influence the stock price of various firms operating in energy companies, including regulatory policies, technological changes, and regional energy demand. Furthermore, the addition of sector-specific indicators, such as the rate of renewable energy diffusion or the changes in government subsidies, could enhance predictability for firms involved in green energy. This flexible framework helps stakeholders position themselves in the wider perspective of stock movements within the energy sector for informed strategic decisions.

Policy and Strategic Recommendations

To energy stakeholders, financial challenges in crises need strategic navigation through data-driven insights. Policymakers and industry leaders should work toward establishing frameworks that build resilience against market volatility. First, there is a need to increase transparency in the pricing of energy and supply chain management. With better visibility into how the price mechanism works and where potential supply chain ruptures may occur, stakeholders are better able to manage their expectations and subdue panic-style market reactions. Contingency planning, by which specific courses of action could be identified under different crisis scenarios, potentially mitigates many negative consequences caused by sudden and dramatic market swings.

Moreover, strategic research and development investments should be made to drive innovation in energy efficiency and renewable technologies. In this way, diversification away from fossil fuel dependency insulates these companies from the wild fluctuations that traditionally have taken place in energy markets. Policymakers could further provide incentives to corporate entities for the implementation of sustainability initiatives-the outcome of which most likely will be stability for these corporations in stock and investor perceptions over a very long time. Collaboration between public and private sectors in sharing information gained through predictive modeling improves knowledge bases across this market and better prepares the sector. Building adaptability and a spirit of innovation into the culture will more firmly equip energy sector stakeholders to resist financial stress in crises, thus making it easier to develop a truly resilient and sustainable energy future.

VII. Discussion

Broader Implications

There are great opportunities in the integration of machine learning and financial forecasting to improve predictive accuracy, especially in these volatile markets where prices fluctuate rapidly with immense uncertainty. Indeed, through the enlarged computational capability to scrutinize a load of data with capabilities that make them more observant of all complex patterns the classic ones usually miss, their contribution to raising predictive efficacy is rather significant. For example, this could be achieved using machine learning models that dynamically adjust to changing market conditions based on historical price data, trading volumes, and external factors such as economic indicators and geopolitical events. This makes the forecasts more responsive and thus helps investors and analysts make timely decisions based on the latest market trends. Besides, machine learning can be seen to continue gaining from fresh information, enabling this model to only get better, refining its prediction as more information becomes available. This perspective orientation not only enhances the forecasting precision but may also give significant insight to those operating in the markets due to better explanations of the driving forces, helping them decide better on investment matters.

Predictive models might also be put into practice by decision-makers within several finance-related spheres to great avail. In this regard, investment firms could practice machine learning for portfolio management by way of automated trading based on market signals in real-time. This would minimize a lot of the human biases and emotional decisions which are common catalysts for market volatility. Additionally, financial institutions can use such models to accurately determine risk, thus making informed decisions on lending and investment. The insight from machine learning can also contribute to regulatory compliance by providing analytics that are more advanced in helping institutions adhere to constantly changing regulations. In all, machine learning in financial forecasting has bigger implications than mere prediction: a sea-change approach to decision-making that improves efficiency reduces risk, and engenders resilience in volatile markets.

Challenges and Limitations

While machine learning indeed has several promising developments to contribute to financial forecasting, challenges, and limitations remain prominent, especially regarding the quality of the data and the adaptability of the models when there are extreme conditions in the financial market. One of the primary concerns lies in the availability and integrity of the data. Many financial markets often go through abrupt changes because of unexpected events that might emanate from political crises, economic shock, and others, which can make the data missing or inconsistent. In such cases, historical data used to train machine learning models may not represent the future well, which again means the model may not generalize in extreme situations. This fact underlines the need for robust model validation against a wide range of historical scenarios, including normal and extreme market conditions.

Another limitation is related to model generalizability and scalability. Many machine learning models work great for specific contexts but at once become poor performers when they are let loose into application on some other markets or asset classes. Fundamentally, the features and relations driving prices within one sector may not hold within another sector fact that ultimately makes the task of devising universally applicable models complex. Besides, a model can result in overfitting, and with increasing complexity, one is always getting closer to losing the main ability to have good performance and deliver correct results on new and unseen data. This challenge has raised flags for continuous research and development processes to be sought out for approaches that make enhanced model scalability possible with increased generalizability without compromising predictiveness. Meeting these challenges is important if machine learning is to remain a feasible and useful tool for financial forecasting in complex and volatile markets.

Future Research Directions

The path ahead is reasonably motivating, as much more can still be done to improve financial forecasting using real-time information and complex algorithms. Real-time data streams, for example, come from social media sentiment analysis, macroeconomic indicators, and market news. If put together, all this will add context and therefore power to machine learning models for better predictions. By harnessing this flow of information, researchers can construct algorithms that are not only sensitive to historical trends but also react to current events and sentiments that can influence market fluctuations. This movement into real-time analytics is a great evolution in financial forecasting, with the ability for more timely and relevant predictions amidst an increasingly rapid market environment.

Another promising avenue of improvement in predictive accuracy is the exploration of integrating multimodal data. Combining insights from multiple types of data, such as quantitative financial data, textual news reports, and images related to market graphs, better frames the models for wide capturing of determinants. For example, natural language processing methods allow researchers to track the sentiment in news stories and changes that might subsequently take place in the prices of securities. Equally important are images of the market graph to reveal some emerging patterns of trading trends. Such a combination of disparate data types can give a fuller view of market dynamics and enhance predictive model robustness. As machine learning capabilities continue to evolve, embracing these innovative approaches will be key to pushing the boundaries of financial forecasting and addressing the complexities inherent in volatile markets.

IX. Conclusion

The main purpose of this study was to assess the effectiveness of different machine learning models in predicting stock price movements during an energy crisis. This research investigated the stock price fluctuations of Shell during the energy crisis, considering historical data and machine learning techniques to identify patterns and trends. The dataset for this study was sourced from accredited and credible sources providing a more detailed view of how the variation in stock prices of major energy firms was influenced by different energy crises that occurred during the period 2021-2024. The proposed three big energy companies listed under their abbreviations for convenience comprise ExxonMobil (XOM), Shelll-SHEL, and BP-BP; after which historical data was gathered using y-finance. This dataset was of great help to analysts interested in financial analysis, market behavior, and the impact of global events on the energy sector. The data consisted of the daily adjusted closing prices of the selected companies from January 2021 to date. Models like Logistic Regression, Random Forest classifiers, and Support Vector Machines classifiers were deployed since they offered distinct strengths and were capable of offering the right potential. The proven performance metric used encompassed Precision, Recall, Accuracy, and F1-Score. The Random Forest model has the highest accuracy at 0.52, followed by Logistic Regression with an accuracy of 0.51, and then the Support Vector Classifier with an accuracy of 0.50. There are great opportunities in the integration of machine learning and financial forecasting to improve predictive accuracy, especially in these volatile markets where prices fluctuate rapidly with immense uncertainty. Predictive models might also be put into practice by decision-makers within several finance-related spheres to great avail. In this regard, investment firms could practice machine learning for portfolio management through automated trading based on real-time market signals. Predictive modeling of the energy crisis brings huge dividends for investors and analysts. The first among the main recommendations is to take advantage of the model predictions within a diversified investment strategy. In this direction, the investors must use the output of those different predictive models not as an isolated lead but as a complementary tool enhancing the traditional analysis techniques.

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