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Evaluating Predictive Power of Fundamental and Technical Indicators Using Machine Learning in Commodity Markets

[1]Anil Kumar Bhagat
Research Scholar, Anand Institute of Management, Bhopal (M.P.)

[2]Vijay Kumar Jain
Professor & Director, Department of Management, Anand Institute of Management, Bhopal (M.P.)

Abstract- Commodity markets are characterized by high volatility and complex price dynamics, making accurate forecasting crucial for effective trading and investment decisions. This study investigates the predictive power of fundamental and technical indicators in commodity markets using machine learning (ML) approaches to enhance forecasting accuracy and trading decision-making. Historical data from Yahoo Finance for commodities including gold, silver, copper, aluminum, and natural gas were analyzed, encompassing price series, volume, macroeconomic variables, and derived technical indicators such as SMA, EMA, RSI, MACD, ATR, and Bollinger Bands. A structured methodology involving data preprocessing, feature engineering, and exploratory analysis was employed to identify price trends, return dynamics, volatility regimes, and market activity patterns. Rule-based signal generation using RSI and MACD produced buy, sell, and hold signals, while ML models Decision Tree, Random Forest, and Gradient Boosting—assessed predictive performance. Model evaluation metrics included accuracy, precision, recall, F1-score, alongside financial measures such as Sharpe Ratio, maximum drawdown, and cumulative return. Results showed varied predictive performance across commodities: Silver achieved perfect classification (accuracy, precision, recall, F1-score = 1.00), Copper Random Forest yielded 99% accuracy with 0.83 F1-score, and Gold Decision Tree achieved 96% accuracy. Integrating technical indicators with machine learning provides a systematic framework for commodity price forecasting, offering actionable insights for risk-adjusted trading strategies in volatile markets.

Keywords- Commodity markets, machine learning, technical indicators, fundamental analysis, price forecasting, trading signals and Decision Tree

1. Introduction

The increasing complexity and volatility of global commodity markets have amplified the need for advanced analytical frameworks capable of generating accurate and timely trading insights. Traditional approaches such as fundamental and technical analysis remain central to market evaluation; however, the rapid expansion of data availability and computational power has shifted modern financial research towards data-driven, machine learning (ML)-based forecasting systems. Within this context, the present study develops and evaluates a hybrid analytical framework that integrates technical indicators, rule-based trading logic, and machine learning classification models to examine the predictive dynamics of major MCX commodities using real-world financial data sourced from Yahoo Finance[1]. The foundation of this computational approach lies in the systematic transformation of raw market data into structured, analytically rich datasets. Historical price series comprising open, high, low, close,

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and volume were collected for key commodities such as gold, silver, crude oil, natural gas, copper, aluminum, and zinc. These datasets were augmented with both technical indicators and selected macroeconomic variables to support a dual analytical framework that reflects both price-driven and external market influences. Preprocessing operations ensured the integrity and consistency of the dataset through the treatment of missing values, outlier detection, duplication removal, and the application of Min-Max normalization [2]. Additional feature engineering steps incorporated trend, momentum, volatility, and volume indicators including SMA, EMA, RSI, MACD, ATR, Bollinger Bands, OBV, and VWAP, thereby capturing multidimensional market dynamics. Technical indicator analysis formed a crucial stage of the methodology, facilitating the extraction of actionable patterns from historical price movements. Trend-following indicators were used to detect directional shifts, while momentum-based metrics provided insights into overbought and oversold conditions. Building on this enriched feature set, a rule-based signal generation mechanism was implemented to translate indicator behavior into structured trading recommendations. By combining momentum confirmation through RSI thresholds with trend validation via MACD crossovers, the framework produced disciplined buy, sell, and hold signals aligned with algorithmic trading principles. This hybrid logic aimed to reduce false positives and improve decision reliability in volatile commodity markets [3].

Figure 1 MCX Trading Chart Analysis [4]

To evaluate the predictive strength of the engineered dataset, two supervised ML models Decision Tree and Random Forest Classifiers were trained using Scikit-learn. The Decision Tree model provided interpretability and explicit rule extraction, while the Random Forest model offered enhanced accuracy and robustness through ensemble averaging and reduced overfitting[5]. Model evaluation employed both statistical and financial metrics, including accuracy, precision, recall, F1-score, MAE, RMSE, Sharpe Ratio, maximum drawdown, and cumulative returns. This multi-dimensional assessment ensured rigorous validation of model performance across predictive and risk-adjusted dimensions. This secton presents a comprehensive data-driven approach that integrates traditional market analysis with modern machine learning techniques, aiming to enhance forecasting precision and support informed trading strategies within the MCX commodity ecosystem [6].

2. Literature Review

Zeng 2025 et al. Analyzes the interconnected risk factors influencing the commodity grain market and the US Climate Policy Uncertainty Index. The significance of systematic risk becomes apparent during times of market stress when results show that quantile spillovers are higher under extreme market situations compared to median levels. The relationship between the central processing unit and grain commodities is found to be diverse across time-frequency scales, according to wavelet coherence analysis. When market circumstances are stable, the CPU's ability to foresee hazards in segmented grain markets is not as strong as it is in extreme cases. Furthermore, spillovers between central processing unit (CPU) and main grain commodities differ among quantile states and are immensely influenced by climate change. These results provide useful information for developing-world politicians as they craft climate and agriculture policies, and for investors looking to mitigate climate-related risks. Stakeholders can alleviate the impact of climate policy uncertainty on grain commodities markets by gaining a better knowledge of the quantile-dependent and heterogeneous risk dynamics.[7].

Dogah 2024 et al. Using quantile regression, it analyzes how CPU affects energy and metal commodity futures markets in normal, bullish, and bearish market situations. According to the findings, CPU impacts are conditionally dependent and exhibit heterogeneity. When markets are bearish, CPU has a negative impact on all commodities except natural gas; when markets are normal, it has a variable effect on energy commodities; and when markets are bullish, it exhibits mixed results. A potential climate policy risk that natural gas can mitigate is becoming clear. A crucial transmission mechanism for CPU shocks, according to channel analysis grounded on the theory of store and the hedging pressure hypothesis, is inventory levels. These results show that regulators should include market-based regulations in decarbonization programs and give producers crucial knowledge for managing their inventories. Risk management, hedging choices, and strategic planning in commodities markets vulnerable to changing environmental rules can be improved by gaining a better understanding of the market- and commodity-specific reactions to climate policy uncertainties [8].

Billah 2024 et al. Using a new framework based on CAViaR and QVAR approaches for hedging and portfolio strategies, this study investigates the linkages of downside risk between green bonds to Islamic sectoral markets. Regardless of the market situation, the results show a high degree of downside risk connectivity and spillovers, with the former having more impact in the near run than the latter. The Shale Oil Revolution, the recent trade tensions between the US and China, the COVID-19 epidemic, and the conflict between Russia and Ukraine are some of the significant events that have an impact on these relationships, and these links change over time. Under moderate to high downside risk across many frequencies, green bond indices in the Chinese market, the EU, the US, and global markets mainly receive net shocks, while green bonds in the US and globally operate as net transmitters in some risk scenarios. Shock transmitters are Islamic sectors markets like BM, OG, FIN, CG, and HC, and receivers are TELE and UTL. Depending on the frequency and severity of downside risks, CS, INDUS, and

TECH play different roles in the sector. The results shed light on how to handle risk, diversify a portfolio, and strategically hedge when faced with volatile markets.[9].

Ayben 2023 et al. In order to forecast the Istanbul Borsa 100 (BIST100) stock price index and the price spreads on 5-year term CDS, a simulation model was developed using a combination of artificial intelligence methods. To examine the correlations between variables both in the short and long term, we employed nonlinear econometric models as the Kapetanios, Shin, and Snell tests, as well as an exponential smooth transition autonomous vector error correction model. The dataset, which includes 1211 observations from August 2015 to August 2020, was analyzed using the multilayer perceptron artificial neural network (ANN). There are 25 hidden neurons and 6 input variables in the feedforward backpropagation model, which uses the Levenberg-Marquardt method to get the expected results. Calculations for BIST100 and CDSs were made by the output layer. The simulation's output was compared to the actual values using performance analysis. For BIST100, the average difference was 0.04%, whereas for CDSs, it was -0.163%. The results demonstrate that the ANN performs admirably when it comes to forecasting financial indicators, indicating its suitability for predictive financial modeling.[10].

Ayala et al., 2021 involves making a trading choice by using a technical indicator in conjunction with a machine learning strategy. What makes this method unique is not only that it can be used to other technical indications, but also that the hybrid rules are both easy to use and highly successful. We evaluated the efficiency of ANN, Linear Model (LM), Random Forests (RF), and Support Vector Regression (SVR) to get the best machine learning method. Triple exponentially moving averages (TEMA) or Moving Average Divergence with Convergence (MACD) were taken into account as trading technical techniques. Using trading data from three major indices—Ibex35 (IBEX), DAX, and DJI—we evaluated the resulting approach. The results demonstrate that trading signals and the suggested trading rules become more competitive when machine learning techniques are integrated with technical analysis methodologies.[11].

Yıldırım et al., 2021 The foreign currency (Forex) market is unique among financial markets in that it offers traders substantial potential rewards along with substantial risk. Since all traders need to do to make money in this market is guess where the value of two currencies will go in relation to one another, it is incredibly straightforward. Nevertheless, compared to other conventional financial markets, the stakes for making a wrong forecast in Forex may be substantially larger. This problem is distinct from the norm when it comes to time-series forecasting due to the need to predict the future. For this study, we exploited the direction-predicting capabilities of a well-known deep learning tool—"long short-term memory" (LSTM)—that has proven to be immensely useful in numerous time-series forecasting tasks. In the financial sector, two basic methodologies are fundamental analysis and technical analysis, which use various data sets. For our study, we utilized two pieces of data: macroeconomic data and technical indicator data. Experiments with actual data showed that the hybrid model we suggested—which merges two independent LSTMs that responded to these two datasets performed admirably.[12].

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Y. Li et al., 2021new Combining the BiGRU deep learning model with VMD and the iterated cumulative sum of squares algorithm, a hybrid forecasting approach called BiGRU-iterated cumulative sums of squares (ICSS) is suggested. In order to effectively predict price movements in the gold futures market, the forecasting framework can identify shifts within market conditions, deconstruct its interaction with external markets, and extract the underlying reasons and patterns within the market. The experimental results demonstrate that the hybrid forecasting method outperforms the benchmarks in terms of prediction performance. We also develop trading strategies and evaluate their effectiveness in the gold futures market by expanding the suggested hybrid forecasting method. Results from tests conducted over an 11-year out-of-sample period (2008–2019) show that the strategy developed using the proposed approach consistently outperforms other popular trading strategies across a range of market conditions and generates high levels of positive returns. When applied to the spot gold market in general, the method consistently produces superior results, which can be useful for reducing investment risk and developing hedging strategies in the gold commodity market.[13].

Dadhich et al., 2021 This research aims to use an econometric prediction model to try to unravel the feasibility of predicting the stock prices of the two main Indian indexes, the BSE and the NSE. This was achieved by retrieving the daily closing statistics of the chosen indices from their respective websites. Research Approach: In order to make the series stationary and find if there is a unit root, the ADF test is used. After determining that the first difference between the GARC H, ACFs, and PACFs values in the correlogram was small, we find that the residual of the ARIMA model we chose is white noise. From among the top twenty best results, the ARIMA forecasting model for DLOG_BSE was selected using model (3, 1, 2), whereas for DLOG_NSE, the best forecasting model was discovered using (0, 1, 4). Results: The optimal model for predicting the chosen indices from 1 March 2018 to 28 March 2018 was determined after considering 474 data, and the results of comparing the predicted and actual performance of both indices were satisfactory. Potential uses of this research: The potential suggestion Since the research is based on daily closing value rather than weekly or monthly data, investors can make more informed trades using the ARIMA model to predict future stock price changes. What makes this study unique or novel: In order to predict the time series data's daily closing price, the study details the best-fitting equation, which emphasized the strength of the ARIA model. In conclusion, these models are the most effective predictive tools for making short-term value predictions, and they unquestionably help investors choose the best portfolio strategy and a wide range of investments.[14].

Dutta et al., 2021 . In view of the national government's intentions to drastically cut CO2 emissions through the implementation and financing of a wide range of environmentally friendly infrastructure and green projects, green investment has lately garnered a lot of interest in India. It is necessary to accurately estimate the time-varying volatility of these green stocks in order to comprehend their underlying risk, since investment in eco-friendly projects is still in its infancy in India. Consequently, the stock prices of Indian green companies may be extremely volatile and susceptible to risk transmission from other assets. Using a GARCH-based quantile regression approach based on daily data, we investigate whether the stock volatility of Indian green enterprises can be forecasted using the information contents of commodity-based implied volatility indices (VIX). The results demonstrate that different green stock indices in India are highly susceptible to risk transmission from the crude oil, gold, and silver markets. During periods of high uncertainty, green stock indexes were more likely to receive volatility from the commodities and precious metal markets, as the transmission from commodity-based VIXs is stronger during bearish stock market periods compared to rising stock market periods. Socially responsible investors can utilize our findings to better understand how a company performs financially and environmentally [15].

3. Research Methodology

This study adopts a comprehensive research methodology that integrates fundamental, technical, and machine learning (ML) approaches to enhance the accuracy of commodity market forecasting and trading strategies. Historical commodity data sourced from Yahoo Finance serves as the foundation for analysis, encompassing price series, derived technical indicators, and macroeconomic variables. The research process involves systematic data preprocessing, feature engineering, and exploratory data analysis to uncover price behavior, return dynamics, and volatility regimes. Technical indicators are applied to extract trend and momentum patterns, followed by rule-based signal generation for buy, sell, and hold decisions. Finally, machine learning models such as Decision Tree and Random Forest are implemented to evaluate predictive performance, supported by rigorous model evaluation metrics like accuracy, precision, recall, and F1-score. This structured methodology ensures reliable, data-driven insights for commodity price prediction and trading optimization.

A. Data Source

The datasets were obtained from Yahoo Finance, containing historical data for commodities such as gold, silver, copper, aluminum, crude oil, natural gas, and zinc. Each dataset includes:

- Historical price series (Open, High, Low, Close, Volume)
- Derived technical indicators
- Macroeconomic and global market variables

This data supports the dual analytical framework of fundamental and technical evaluation.

B. Data Preprocessing

Data preprocessing was an essential step to ensure clean, consistent, and analytically usable inputs for the machine learning models. Raw historical price and volume data sourced from Yahoo Finance were cleaned by handling missing values through interpolation/forward-fill and removing duplicates or statistical outliers. Feature engineering was performed to enrich the dataset with technical indicators, including SMA, EMA, RSI, MACD, ATR, and Bollinger Bands, capturing trend, momentum, and volatility characteristics. All continuous variables were normalized using Min-Max scaling to standardize feature ranges and optimize model training stability. Finally, the processed data were split into training (80%) and testing (20%) sets to ensure unbiased evaluation of model generalization. These steps converted the raw commodity records into a structured dataset suitable for robust predictive modelling.

C. Initial Data Exploration

The initial data exploration provides a comprehensive understanding of commodity market behavior by analyzing price trends, return dynamics, volatility patterns, and market activity. This stage identifies key price movements, including trends, reversals, and support/resistance zones, offering insights into underlying market structures. Through return and volatility analysis, the study examines stability, risk, and trading intensity, while volume–value relationships highlight liquidity and market efficiency across different commodities.

1. Price behaviour (commodity wise): Identify trends, reversals, support/resistance zones, and price regimes.

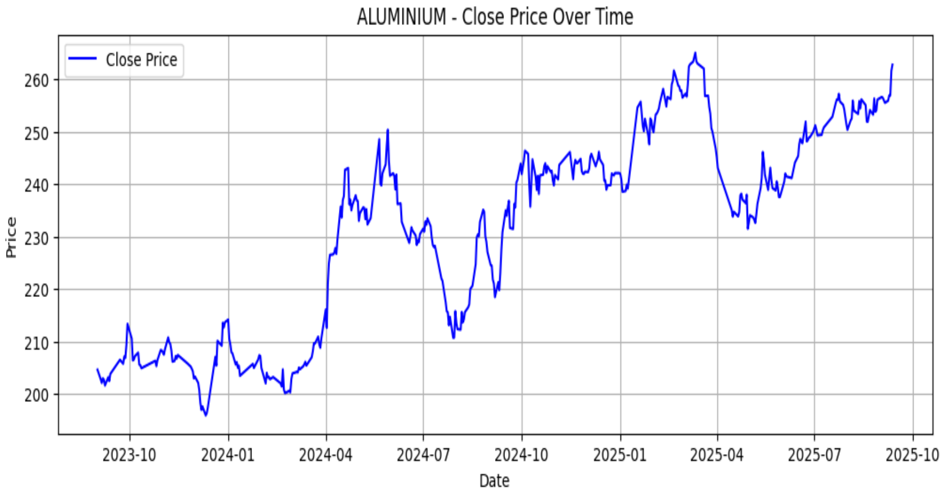

Figure 2 Aluminium-Close Price Over Time

Aluminium: Shows steady uptrend with periodic corrections; support near 210, resistance around 260; cyclical reversals evident.

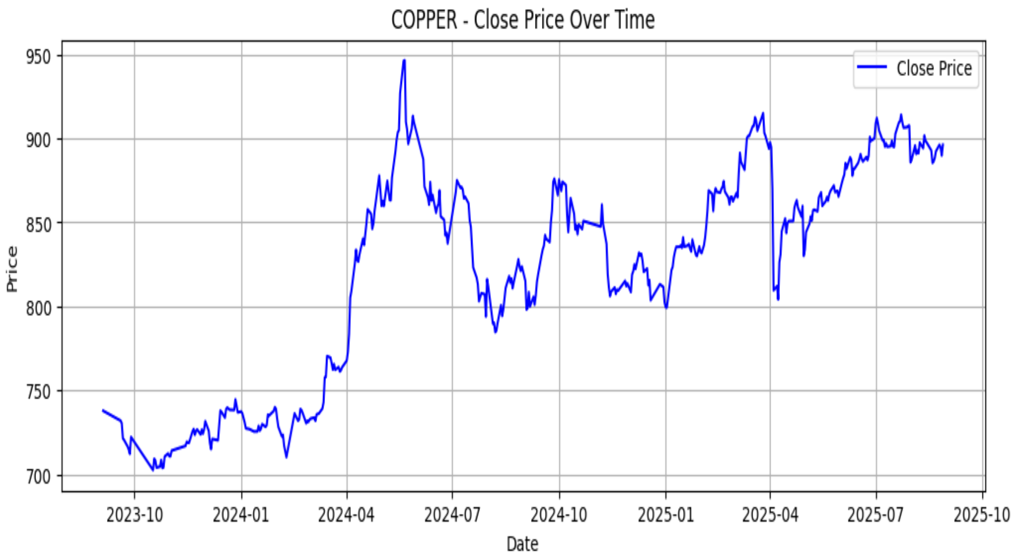

Figure 3 Copper-Close Price Over Time

Copper: Gradual bullish trend with volatility spikes; strong support ~780, resistance ~900; multiple short-term pullbacks

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2. Analysing Return Dynamics

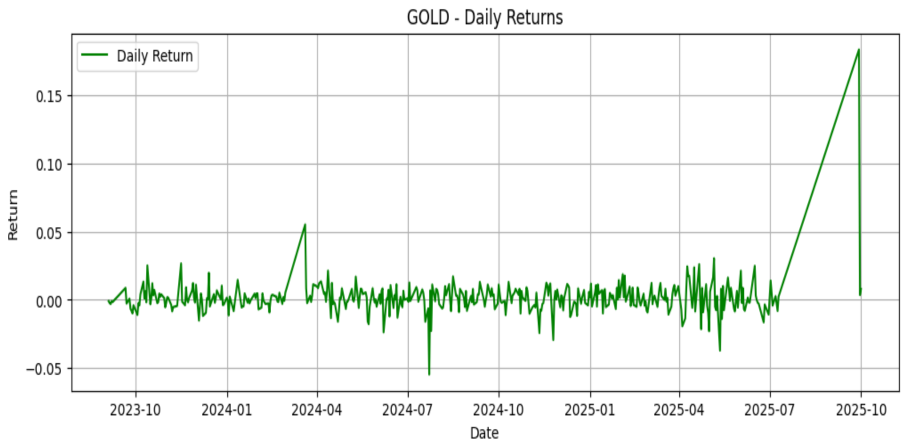

Figure 4 Gold-Daily Return

Mostly stable returns with a sharp mid-2025 spike above 0.15, indicating rare but significant positive price movement.

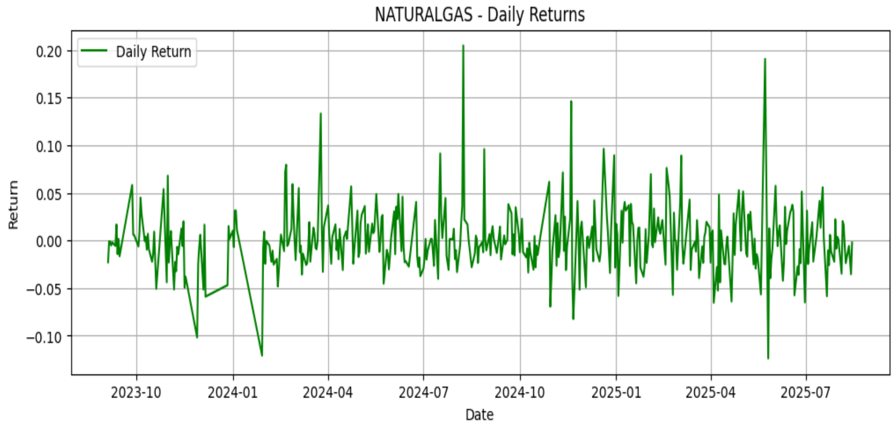

Figure 5 Natural gas Daily Return

Highly volatile returns, ranging from -0.10 to 0.20, with frequent spikes-suggesting speculative trading and reactive price movements.

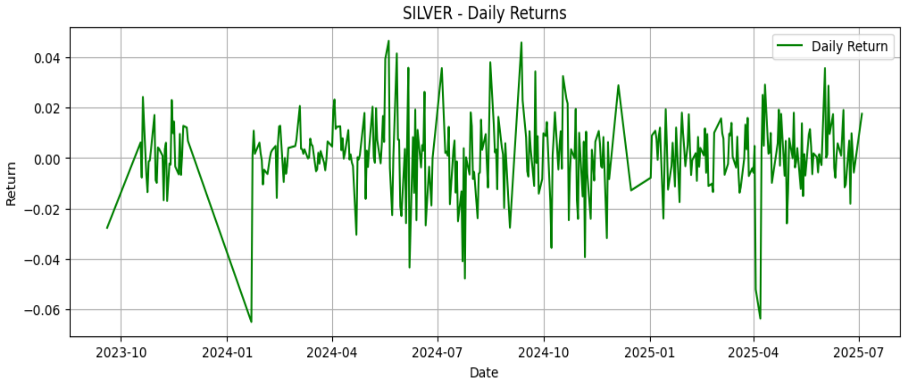

Figure 6 Silver Daily Return

Returns fluctuate within ±0.06, showing consistent volatility; no major outliers, indicating active but relatively balanced market behavior.

3. Assessing Volatility Regimes: Plot 20-day rolling standard deviation.

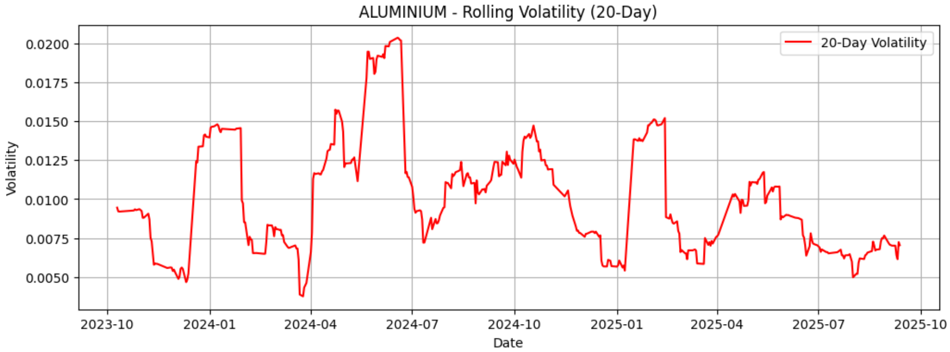

Figure 7 Aluminium- Rolling Volatility (20 Days)

Volatility oscillates between 0.005–0.020, showing periodic spikes-suggesting alternating calm and reactive phases in aluminium price behavior.

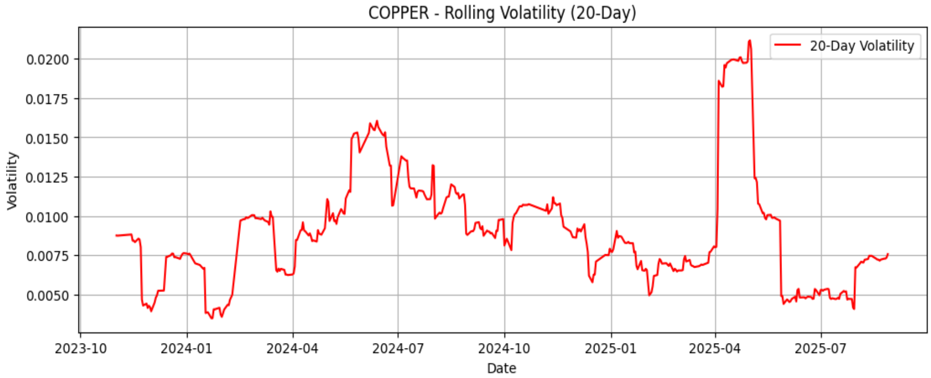

Figure 8 Copper-Rolling Volatility (20 days)

Volatility remains subdued until early 2025 spike, then drops sharply-indicating a brief disruption followed by market stabilization.

4. Evaluating Market Activity: Scatterplot of Volume (Lots) vs Value (Lacs)

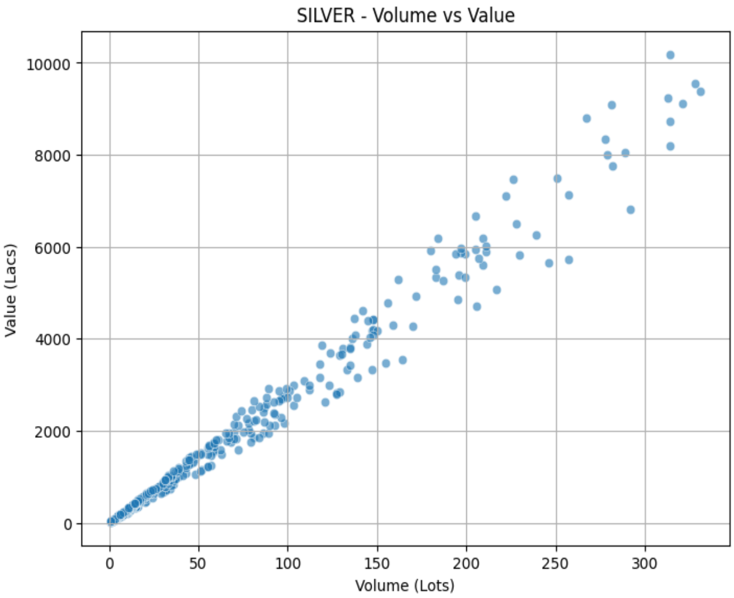

Figure 9 Silver Scatterplot of Volume (Lots) vs Value (Lacs).

Clear upward trend-value increases with volume, highlighting silver's liquidity and consistent valuation across trade sizes.

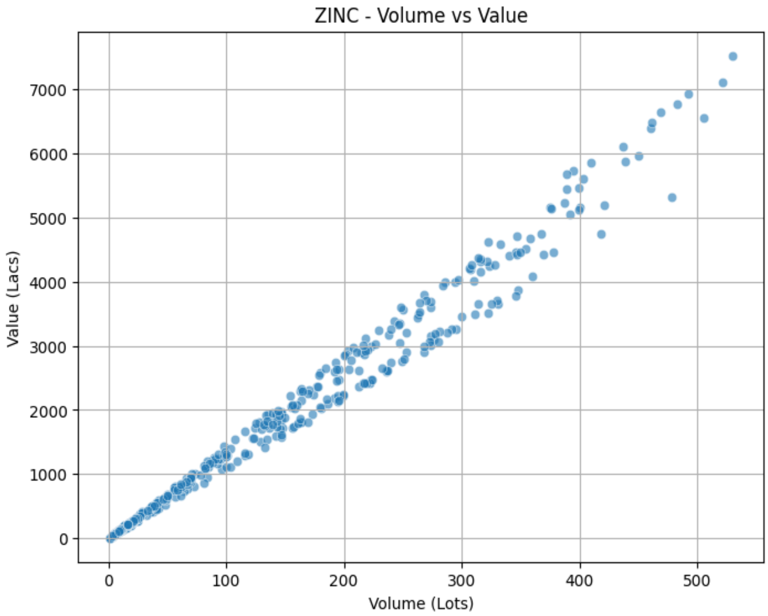

Figure 10 Zinc Scatterplot of Volume (Lots) vs Value (Lacs)

Dense linear clustering-volume strongly predicts value, reflecting stable pricing and high transparency in zinc market activity.

D. **Technical Indicator Analysis**

Technical indicator analysis was performed to extract actionable patterns from historical price data and support trend-based modeling. Indicators were computed using TA-Lib, enabling efficient derivation of measures related to trend, momentum, volatility, and volume. The technical analysis workflow is designed as a structured, multi-step process that enables systematic evaluation of commodity price behavior and market trends. The analysis begins with iterative multi-asset processing, where each commodity is analyzed individually, ensuring a scalable, asset-wise approach with consistent logic across the dataset. Following this, technical indicators are applied, including trend indicators such as SMA, EMA, and MACD; momentum indicators like RSI and Stochastic Oscillator; volatility measures such as Bollinger Bands and ATR; and volume-based indicators like OBV and VWAP. Utilizing the robust TA-Lib library, this step provides a feature-rich foundation suitable for machine learning or rule-based trading strategies, candlestick patterns such as Doji, Hammer, and Engulfing are detected, adding price action intelligence that captures market psychology and reversal signals, which can be used for confirmation or noise reduction. Support and resistance levels are identified using rolling min/max calculations over a 20-day window, offering key price points for breakout or bounce strategies and enhancing risk management. Buy and sell signals are generated by combining momentum and trend conditions (e.g., RSI and MACD), reducing false signals and allowing integration with candlestick or support/resistance filters.

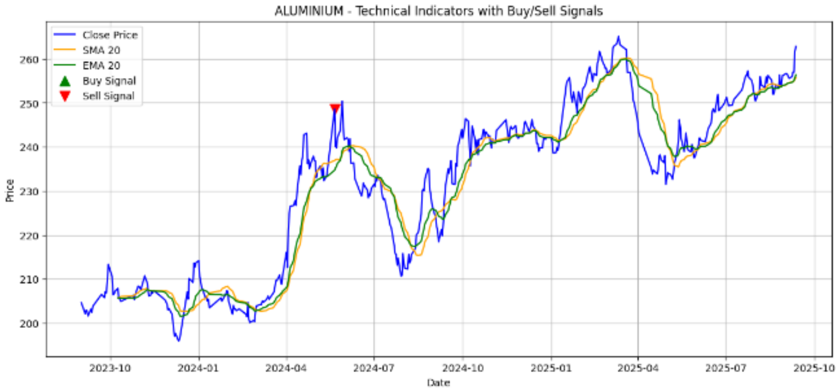

Figure 11 Aluminium- Technical Indicator wit Buy/sell Signals

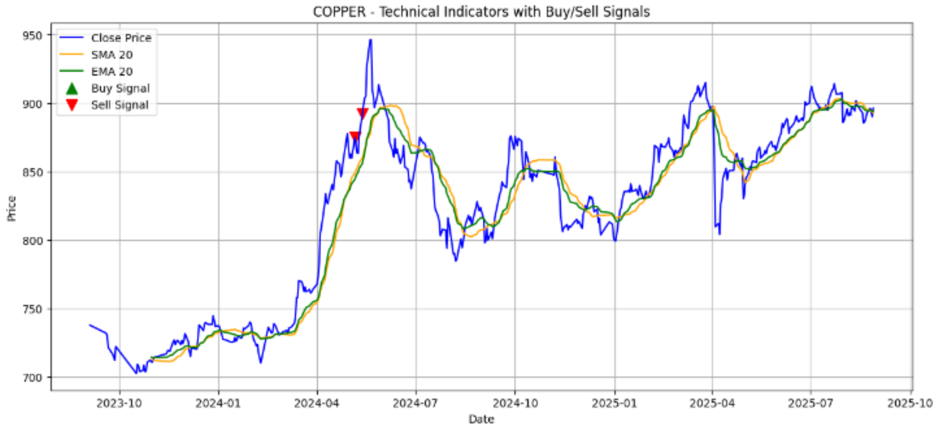

Figure 12 Copper- Technical Indicator wit Buy/sell Signals

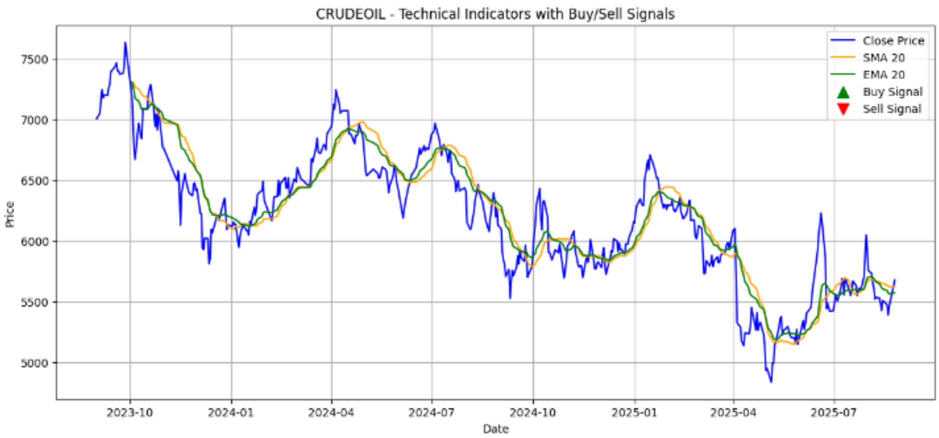

Figure 13 Crude Oil- Technical Indicator wit Buy/sell Signals

E. Signal Generation

A structured rule-based framework was developed to generate trading signals by integrating trend and momentum confirmations. Predefined indicator thresholds were used to classify market actions as buy, sell, or hold. A buy signal was issued when RSI fell below 30 and the MACD line crossed above the signal line, indicating oversold conditions with emerging upward momentum. A sell signal was triggered when RSI exceeded 70 and MACD crossed below the signal line, reflecting overbought conditions and potential downward movement. A hold signal was assigned when none of the criteria were met. This systematic approach ensured consistent and replicable signal generation while reducing false positives by combining momentum (RSI) and trend validation (MACD), aligning the methodology with established algorithmic trading practices.

F. Machine Learning Model Implementation

Machine learning models were implemented to assess the predictive capability of technical indicators and generate directional trading insights. A classification framework was adopted, with the target variable representing price movement (Up/Down). Two supervised algorithms Decision Tree Classifier and Random Forest Classifier were developed using Scikit-learn. The Decision Tree model was selected for its interpretability and ability to capture nonlinear feature-target relationships through recursive partitioning. The Random Forest model, an ensemble of multiple randomized trees, was employed to enhance robustness, reduce overfitting, and improve generalization. Both models were trained on the preprocessed dataset using engineered technical indicators as input variables. Their performance was evaluated using accuracy, precision, recall, and F1-score, supplemented by financial metrics such as the Sharpe ratio during back testing. These models provided a computational framework for evaluating how effectively machine learning captures market dynamics and supports data-driven trading and risk-management strategies.

G. Model Evaluation Metrics

Model evaluation metrics are essential to assess the predictive performance, reliability, and robustness of machine learning (ML) models used for commodity forecasting. In this study, model performance was evaluated using four primary classification metrics Accuracy, Precision, Recall, and F1-Score—to measure how effectively each model predicted directional price movements across multiple commodities. Accuracy quantified the overall correctness of predictions, while Precision indicated the proportion of correctly predicted positive movements out of all predicted positives, reflecting the model's ability to avoid false signals. Recall measured the model's sensitivity in identifying true positive cases, particularly important for capturing significant market shifts. The F1-Score, as the harmonic mean of precision and recall, provided a balanced performance measure by accounting for both false positives and false negatives. These metrics collectively ensured a comprehensive evaluation of each algorithm's predictive quality. Furthermore, a comparative analysis was conducted across models such as Decision Tree, Random Forest, and Gradient Boosting to determine the most effective approach for MCX commodity forecasting and trading optimization. This systematic assessment facilitated the identification of the model offering the highest predictive consistency and practical applicability in data-driven trading strategies within volatile commodity markets.

4. Results And Discussion

This section presents the findings derived from the integration of technical analysis, signal generation, and machine learning modelling for commodity market forecasting. The results illustrate how rule-based trading signals and ML algorithms perform across different commodities in predicting market direction and optimizing trading decisions. Through detailed evaluation of model accuracy, financial metrics, and comparative performance, the analysis

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highlights each model's predictive strength, reliability, and practical applicability in real-world commodity trading.

1) Accuracy

Accuracy measures the proportion of correct predictions made by a model compared to the total number of predictions, providing an overall assessment of how effectively the model classifies data.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (1)$$

2) Precision

Precision indicates the percentage of true positive predictions among all positive predictions, showing how accurately the model identifies relevant cases without including false positives.

$$Precision = \frac{TP}{TP+FP} \quad (2)$$

3) Recall

Recall measures the proportion of actual positive cases correctly identified by the model, highlighting its ability to detect important events or minimize false negatives in classification tasks.

$$Recall = \frac{TP}{TP+FN} \quad (3)$$

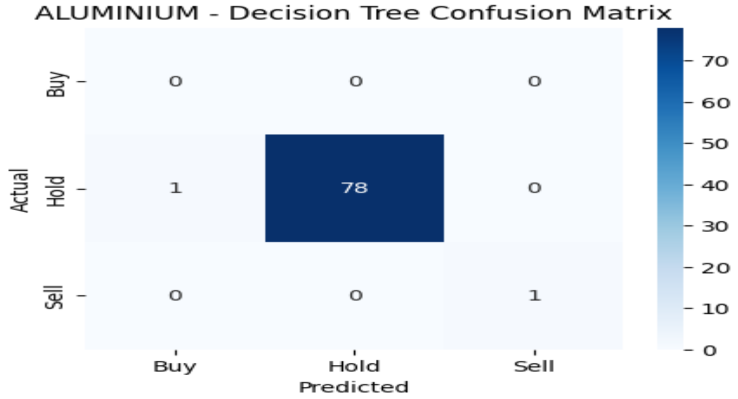
4) F Score

F1-Score represents the harmonic mean of precision and recall, balancing both metrics to provide a single, comprehensive measure of a model's overall classification performance and reliability.

$$F1 - score = \frac{2}{\frac{1}{precision}+\frac{1}{recall}} \quad (4)$$

4.1 Commodity Modelling Workflow

The commodity modelling workflow integrates signal generation and performance evaluation, using technical indicators like RSI and MACD to create rule-based buy, sell, and hold signals, supported by financial performance metrics for trading assessment. The workflow further incorporates financial performance metrics to assess the effectiveness of the generated signals, including the Sharpe Ratio to evaluate risk-adjusted returns, maximum drawdown to capture the worst-case portfolio loss, and cumulative return to track overall portfolio growth over time.



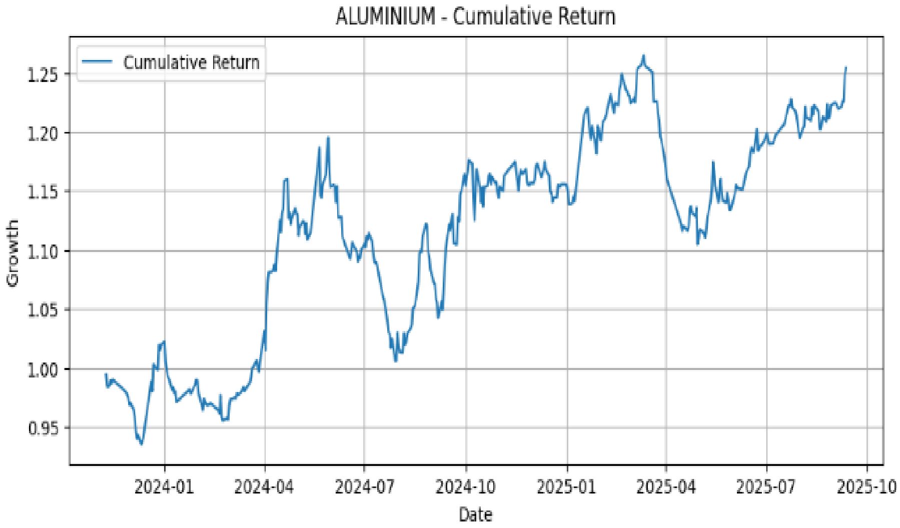
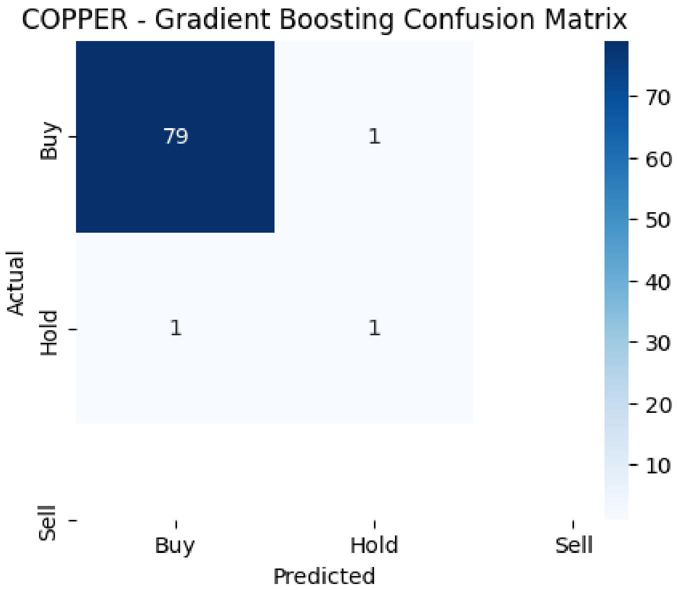


Figure 14 Aluminium Decision Tree accuracy and returns

The aluminium decision tree model demonstrates poor classification performance, as shown by its confusion matrix-predicting "Hold" for nearly all instances and failing to identify any "Buy" or "Sell" cases. This suggests either severe class imbalance or overfitting. Financial metrics further reinforce weak investment appeal: a low Sharpe Ratio of 0.04 indicates minimal risk-adjusted return, a substantial max drawdown of -15.83% reflects high downside risk, and a modest cumulative return of 1.25% implies limited profitability. Overall, the model lacks predictive robustness and the asset shows constrained financial attractiveness. Aluminium cumulative return fluctuates modestly, peaking near 1.25-indicating limited growth, intermittent momentum, and subdued long-term investment appeal.



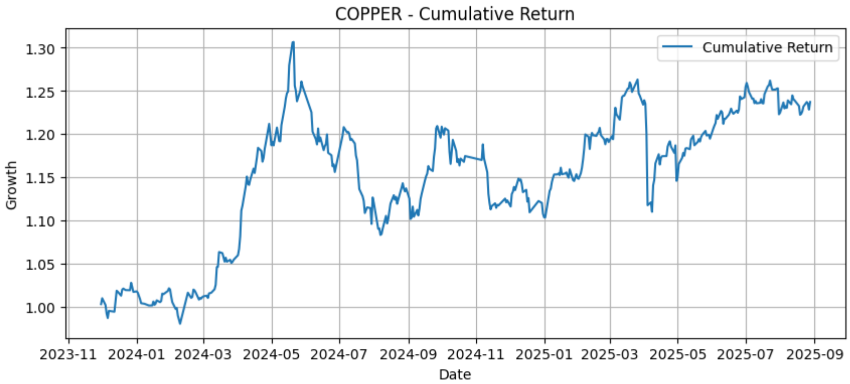
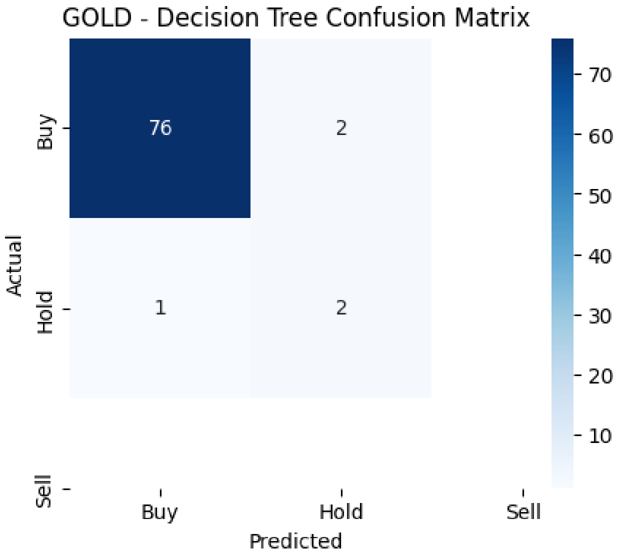


Figure 15 Copper Gradient Boosting accuracy and returns

The Gradient Boosting model for copper shows strong "Buy" prediction accuracy but misclassifies "Hold" frequently. Financial metrics reveal low Sharpe Ratio (0.04), deep drawdown (-17.08%), and modest cumulative return (1.24), indicating limited risk-adjusted performance and unstable investment potential.



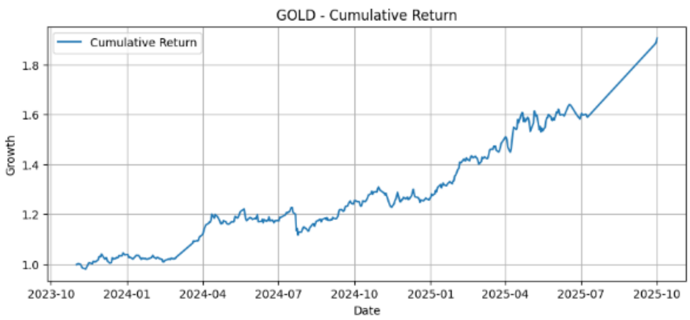


Figure 16 Gold Decision Tree and returns

The decision tree model for gold shows strong "Buy" prediction accuracy. Financial metrics indicate moderate risk-adjusted performance: Sharpe Ratio 0.11, Max Drawdown -9.04%, and Cumulative Return 1.91-suggesting relatively stable growth with manageable downside risk over time.

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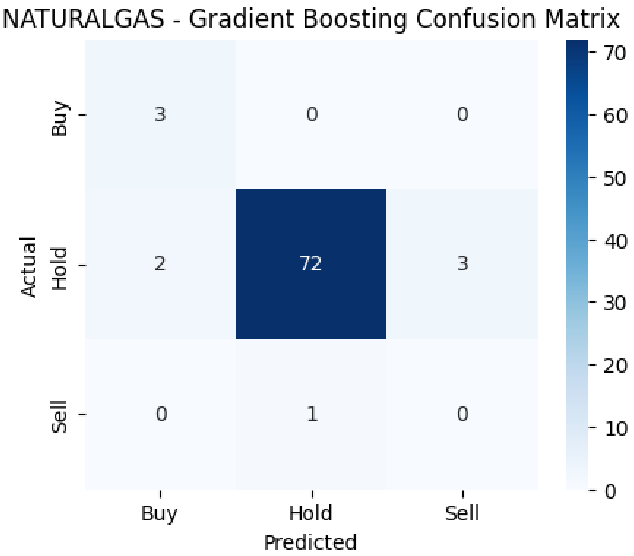

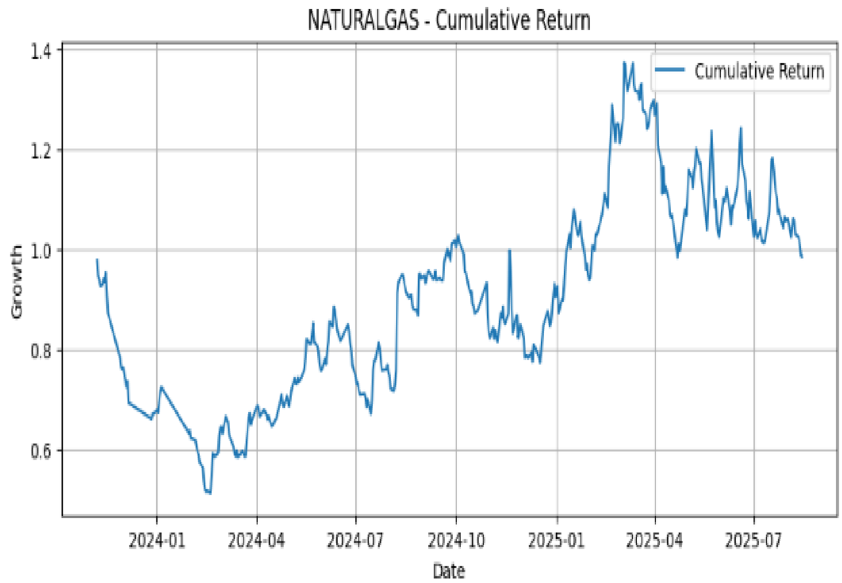

Figure 17 Natural Gas Gradient Boosting accuracy and returns

The Gradient Boosting model for natural gas shows limited predictive diversity, heavily favoring "Hold" with minor misclassifications. Financial metrics reveal poor performance: Sharpe Ratio 0.01, Max Drawdown -47.78%, and Cumulative Return 0.98-indicating high risk, minimal reward, and weak investment viability despite brief mid-2024 growth.

4.2 Machine Learning Model Results

The machine learning model results section presents the predictive performance of various algorithms applied to commodity market data to evaluate their forecasting accuracy and trading potential. Three supervised models Decision Tree, Random Forest, and Gradient Boosting were implemented and compared across five commodities: Aluminium, Copper, Gold, Natural Gas, and Silver. Due to insufficient class diversity, Zinc and Crude Oil were excluded from model testing. Each model's effectiveness was assessed using Accuracy, Precision, Recall, and F1-Score, providing a comprehensive measure of predictive reliability and consistency.

ML modelling was not applicable to ZINC and CRUDEOIL because of insufficient class diversity for stratified split.

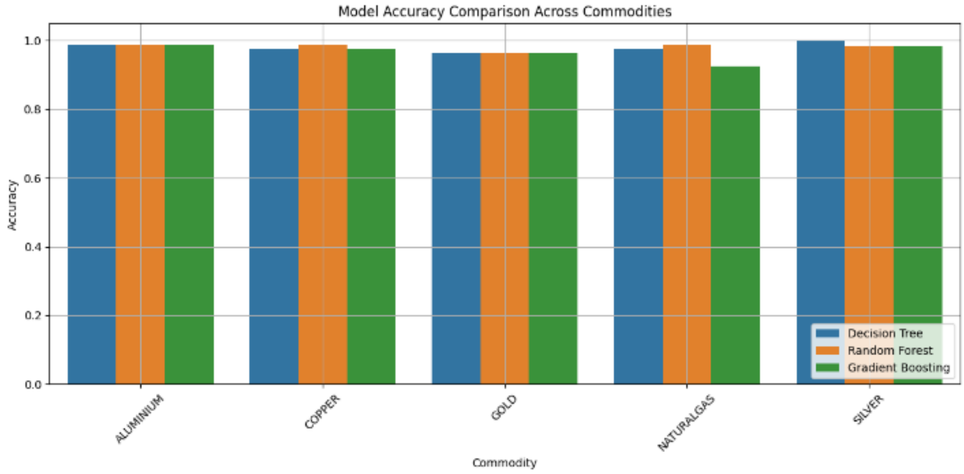

Figure 18 Model Accuracy Comparison across Commodities

The bar chart compares model accuracies across five commodities-Aluminium, Copper, Gold, Natural Gas, and Silver-using three algorithms: Decision Tree, Random Forest, and Gradient Boosting. Overall, all models perform with high accuracy near 1.0, with Random Forest slightly outperforming others, especially for Natural Gas and Silver, indicating strong model consistency across commodities.

Table 4. 1 Performance metrics of best models for commodity prediction

Commodity	Best Model	Accuracy	Precision	Recall	F1 Score
ALUMINIUM	Decision Tree	0.99	0.67	0.66	0.66
COPPER	Random Forest	0.99	0.99	0.75	0.83
GOLD	Decision Tree	0.96	0.74	0.82	0.78
NATURALGAS	Random Forest	0.99	0.66	0.67	0.66
SILVER	Decision Tree	1.00	1.00	1.00	1.00

The table presents the performance of the best predictive models for five commodities. For ALUMINIUM, a Decision Tree achieved 99% accuracy but moderate precision, recall, and F1-score (~0.66), indicating some misclassifications despite overall correctness. COPPER performed well with Random Forest, achieving high accuracy (99%) and precision (0.99), but lower recall (0.75), suggesting some true positives were missed. GOLD using Decision Tree showed balanced performance with 96% accuracy and F1-score of 0.78, reflecting reliable predictions. NATURAL GAS Random Forest had high accuracy but moderate precision and recall (~0.66). SILVER achieved perfect scores (1.00) across all metrics, indicating flawless prediction performance.

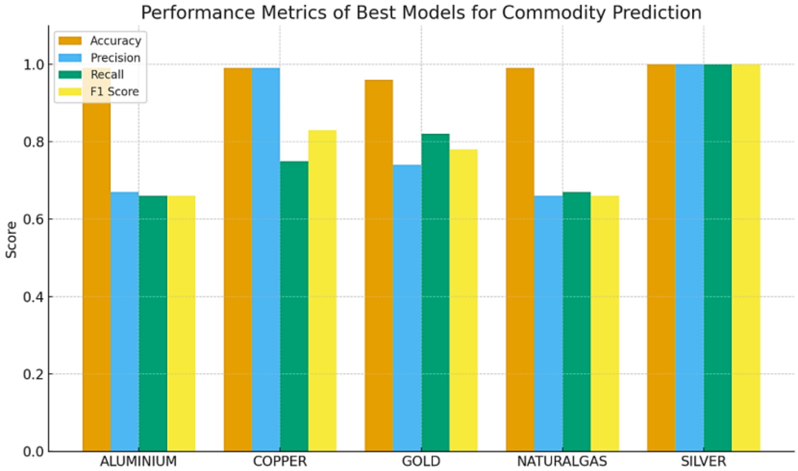

Figure 19 Performance metrics of best models for commodity prediction

4.3 Machine Learning-Based Commodity Analysis

The analysis integrates data exploration, technical analysis, and machine learning (ML) modelling to evaluate commodity price behavior and trading potential. Initial exploration identified trends, reversals, support/resistance zones, and volatility patterns across seven commodities, revealing cyclical uptrends (Aluminium, Gold, Silver), high volatility (Natural Gas, Crude Oil), and moderate fluctuations (Zinc). Return dynamics showed mostly stable trading with occasional spikes, while 20-day rolling volatility highlighted alternating calm and reactive phases. Market activity assessment indicated strong positive volume-value correlations, suggesting active and efficient markets. The technical analysis workflow used SMA, EMA, MACD, RSI, Bollinger Bands, and candlestick patterns to generate rule-based buy/sell signals, visualized with trend overlays. Commodity modelling applied these signals alongside performance metrics (Sharpe Ratio, Max Drawdown, Cumulative Return) to quantify investment effectiveness. ML results revealed varied predictive performance: Aluminium and Natural Gas models favored "Hold" with low Sharpe Ratios and high drawdowns, Copper's Gradient Boosting and Gold's Decision Tree showed moderate profitability, while Silver achieved perfect accuracy and F1-score. Random Forest generally outperformed for volatile commodities. Zinc and Crude Oil were excluded due to insufficient class diversity. Overall, the workflow provided a systematic framework for commodity prediction, combining trend analysis, rule-based signal generation, and ML evaluation for informed trading decisions.

5. Conclusion

The study demonstrates the effectiveness of integrating fundamental, technical, and machine learning approaches to predict commodity market movements and optimize trading strategies. Using historical data from Yahoo Finance and engineered technical indicators such as SMA, EMA, RSI, MACD, ATR, and Bollinger Bands, the research systematically captured price trends, momentum, volatility, and market activity across key commodities, including gold, silver, copper, aluminum, and natural gas. Exploratory analysis revealed cyclical trends, alternating volatility regimes, and strong volume value correlations, which informed structured, rule-based signal generation for buy, sell, and hold decisions. Machine learning models—Decision Tree, Random Forest, and Gradient Boosting evaluated the predictive power of these indicators. Model evaluation using accuracy, precision, recall, and F1-score showed varied performance: Silver achieved perfect prediction with 100% accuracy, precision, recall, and F1-score; Copper Random Forest yielded 99% accuracy, 0.99 precision, 0.75 recall, and 0.83 F1-score; Gold Decision Tree achieved 96% accuracy with 0.78 F1-score. In contrast, Aluminum and Natural Gas models had moderate predictive capability, with Decision Tree for Aluminum showing 99% accuracy but only 0.66 F1-score, and Random Forest for Natural Gas achieving 99% accuracy with 0.66 F1-score, reflecting misclassification challenges. Financial metrics further highlighted risk-adjusted performance, with Sharpe Ratios ranging from 0.01 (Natural Gas) to 0.11 (Gold) and maximum drawdowns reaching -47.78% in highly volatile commodities. The study confirms that integrating rule-based technical analysis with machine learning improves predictive accuracy and informs systematic trading. The results provide a replicable framework for commodity forecasting, risk assessment, and investment optimization in volatile markets.

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