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Time Series Analysis for Commodity Price Forecasting

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ABSTRACT

Commodity price forecasting plays a crucial role in international trade, agriculture, investment, and economic decision-making. However, accurate prediction remains challenging due to market volatility, economic uncertainty, geopolitical events, climate change, and supply chain disruptions. This study proposes a comprehensive time series forecasting framework that integrates classical statistical models, including ARIMA, SARIMA, and Exponential Smoothing, with machine learning and deep learning techniques such as Random Forest Regression, Support Vector Regression, Gradient Boosting, and Long Short-Term Memory (LSTM). The framework incorporates data preprocessing, feature engineering, trend decomposition, stationarity testing, model optimization, and rolling window validation to improve forecasting performance. Model evaluation is conducted using MAE, RMSE, MAPE, SMAPE, and R^2 metrics. Experimental results demonstrate that hybrid forecasting models outperform conventional statistical approaches by effectively capturing nonlinear temporal patterns and improving prediction accuracy under volatile market conditions. The proposed framework offers a scalable, interpretable, and adaptable solution for commodity price forecasting, supporting strategic decision-making, risk management, inventory optimization, and investment planning across diverse commodity sectors.

KEYWORDS

Investment Portfolio Optimization, Portfolio Theory, Mean-Variance Optimization, Risk Management, Asset Allocation, Financial Analytics, Mathematical Optimization, Investment Decision Support, Portfolio Diversification, Risk-Adjusted Return.

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1. INTRODUCTION

1.1. Background

Commodity price forecasting is an important component of the process of decision making in agriculture, finance, manufacturing, energy and international trade. Historically, forecasting was based on statistical techniques including Moving Average (MA), Autoregressive (AR), Autoregressive Moving Average (ARMA), and Autoregressive Integrated Moving Average (ARIMA), which study past price movements and use them to forecast future prices. They can be used to identify linear trends and seasonal fluctuations when the market is stable, due to their mathematical rigor, simplicity, and interpretability. But these days, the modern commodity market is becoming more and more volatile, with climate change, geopolitical conflicts, inflation, global pandemics, trade regulations, supply chain disruptions and demand and supply fluctuations playing a significant role in the volatility. With the advent of big data and artificial intelligence, commodity forecasting has become more dynamic and data-driven, allowing for the analysis of a wide range of data sources such as financial indicators, weather data, satellite observations, and market sentiment. As such, modern machine learning and deep learning techniques have improved forecasting capabilities to deliver more accurate, adaptive and intelligent forecasts that can be used for complex and dynamic commodity markets.

1.2. Evolution of Analytical Portfolio Models

Commodity price forecasting is a crucial application of time series analysis as prices of commodities vary over time and there are very strong time dependencies that need to be carefully considered. Time series analysis is different from conventional analytical approach, which assumes independence of observations, because it takes into account the chronological sequence of the data, which enables the detection of meaningful patterns, e.g. long-term trends, seasonal fluctuations, cyclical movements and irregular fluctuations.

This feature enables researchers and decision makers to gain insights into past market activity and produce more accurate commodity price predictions. Time series analysis is widely used in forecasting agricultural products, energy resources, precious metals, and various other commodities of the financial markets, depending on the conditions of the markets, which are affected by the policies of the economy, climate, demand in the world, geopolitical events and dynamics of the supply chain. Time series analysis can be used to model these temporal relationships accurately, aiding in risk management, strategic planning, investment decisions, and policy formulation. Moreover, the combination of time series analysis and recent machine learning and deep learning technologies has greatly improved the forecasting accuracy, which allows for the creation of intelligent forecasting systems that model linear and non-linear market dynamics. As a result, time series analysis has emerged as an indispensable tool in devising robust, adaptive and data-driven commodity price forecasting models.

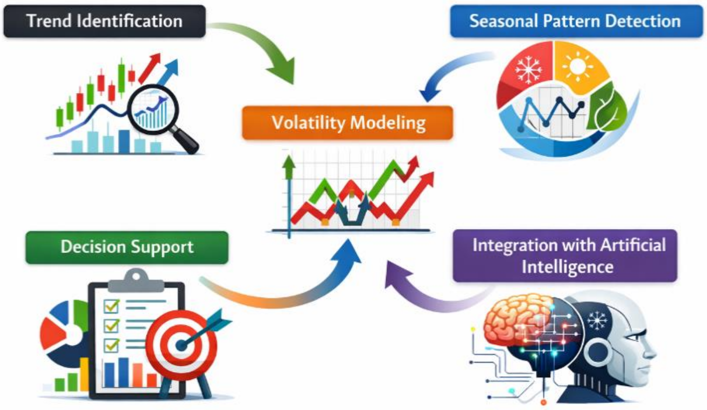

Fig 1 - Evolution of Analytical Portfolio Models

1.2.1. Trend Identification

In time series analysis, one of the key points is the identification of trends, which involves identifying the longer term trend of commodity prices over a long time scale. Market trends can suggest either an upward or downward trend or a relatively flat price increase, depending on the economy, inflation, production capacity, advancements in technology, and consumer demand. The recognition of such long-term trends helps governments, policy makers, investors and businesses make strategic decisions on production planning, investment decisions, pricing policy and market expansion. The accurate trend analysis also helps to detect early the structural changes in commodity markets, which in turn will help to lower financial risks and enhance the reliability of long-term forecasting.

1.2.2. Seasonal Pattern Detection

Seasonal pattern detection looks for regularly occurring price fluctuations, which are caused by predictable environmental and economic factors. The seasonal characteristics of agricultural commodities, including wheat, rice, maize, coffee, and soybean, are frequently influenced by their harvesting cycles, weather, storage conditions, and seasonal consumer demand. These seasonal effects can be removed from the time series using an effective method which isolates the seasonal effects and enables the forecasting models to understand the regular behavior of the market. Forecast systems provide more accurate predictions that can help in agricultural planning and inventory management, market regulation, and resource allocation, and help you better identify seasonal patterns.

1.2.3. Volatility Modeling

Volatility modeling is about studying and forecasting the volatility of commodity prices due to unpredictable events like wars, natural disasters, economic crises, inflation, pandemics, and supply chain failures. Forecasts of a commodity market often suffer from sudden and large model errors in the absence of an adequate model. Time series analysis can offer good tools for describing these irregular price changes and quantifying the uncertainty of the market at different points in time. Precise volatility modelling allows forecasting systems to react better to market volatility, helping investors, traders, financial institutions and policy makers to navigate the market more effectively, reduce risk, increase market stability, and make timely business decisions.

1.2.4. Decision Support

Time series forecasting is a useful decision support tool for governments, financial institutions, business organizations and commodity traders in predicting the behavior of the markets accurately. Good forecasts of commodity prices help policy makers design agricultural policies, safeguard food security, control imports and exports, manage strategic reserves, control inflation and plan economic interventions. In much the same way, private companies use forecasts to inform procurement planning, production scheduling, inventory management, logistics management, pricing and financial investment decisions. Correct forecasting helps to lessen uncertainties, lower operational risks and allocate resources better in the highly competitive and volatile commodity markets.

1.2.5. Integration with Artificial Intelligence

When combined with AI technologies, time series analysis has revolutionized the field of commodity price prediction, allowing for the creation of intelligent forecasting models that can learn from and detect complex temporal patterns in historical data. Machine learning algorithms and deep learning architectures can automatically detect hidden patterns, non-linear dependencies, and changing market dynamics which are hard to identify with traditional statistical methods. The hybrid forecasting models integrate statistical series decomposition and AI-based approaches to enhance the accuracy, adaptability, and robustness of forecasts in various commodity sectors. This integration enables forecasting systems to handle vast amounts of diverse data efficiently and deliver more precise and dependable forecasts for various sectors such as agriculture, financial services, energy, manufacturing, and global trade.

1.3. Time Series Analysis for Commodity Price Forecasting

Time series analysis has emerged as one of the most successful methods for forecasting commodity prices, as it uses a systematic approach to analyze past commodity price observations to forecast commodity market behavior in the future. Prices of commodities are always dynamic and affected by a variety of interconnected factors such as demand and supply, weather, inflation, exchange rate, geopolitical tensions, government policies, transport fares, global economic trends etc. All of these create complicated time series which are best analyzed with techniques that can detect long-term trends, seasonal patterns, cyclical fluctuations and atypical market movements. Time series analysis maintains the temporal dimension of the data, allowing time series forecasting models to incorporate the dynamics of the market's behavior. This attribute makes time series analysis an extremely useful tool for predicting agricultural products like wheat, rice, maize, soybean and coffee, energy commodities like crude oil and natural gas, and precious metals like gold and silver. Today's forecasting models incorporate time series analysis as a tool for estimating future commodity prices as well as finding turning points in the markets, abnormal fluctuations and assessing the influence of external events on commodity markets. In recent years, the technology of big data has developed rapidly, and time series forecasting has gradually shifted from statistical analysis to the use of machine learning and deep learning algorithms to predict intelligently. The more sophisticated models can analyze vast amounts of historical and real-time data, and also learn complex, nonlinear relationships that conventional statistical methods may not detect. In addition, there are preprocessing methods like data cleaning, data normalization, feature engineering, and temporal decomposition that enhance the quality of time series data, resulting in more accurate predictions. The robustness of the forecasting is further improved by rolling window validation and adaptive learning strategies, which continuously update models with information on the market. Accurate time series forecasting helps governments in agricultural planning, food security monitoring and management, inflation control, and development of economic policies; it also enables investors, commodity traders, manufacturers, and managers of the commodity supply chain to optimize procurement, inventory management, production scheduling, and financial risk management. Therefore, time series analysis is the backbone of the new intelligent commodity price forecasting system, which can present reliable, large-scale and data-driven solutions to commodity price forecasting for decision-making in the more volatile global commodity markets.

2. *LITERATURE SURVEY*

2.1. Classical Statistical Forecasting Models

Classical statistical forecasting models have been important tools for predicting commodity prices, as they are based on analyzing past commodity prices to forecast future market trends. The models are widely used because they are mathematically sound, computing efficient and easily explained. In agriculture, finance and energy sectors, Moving Average, Autoregressive, ARIMA, SARIMA and Exponential Smoothing are found to be successfully applied in forecasting commodity prices. They work well to identify the trend, seasonality and temporal patterns in past data and are appropriate for steady markets. They are, however, less effective in forecasting when the commodity markets have sudden fluctuations, display nonlinear behavior or unexpected economic events occur. Therefore, more sophisticated forecasting techniques are needed.

2.2. Machine Learning-Based Commodity Forecasting

In the field of commodity price forecasting, machine learning has revolutionized the process by facilitating the creation of predictive models that can identify complex patterns and relationships in vast amounts of historical and market data. Machine learning models can handle several influencing factors at the same time, such as the market demand, weather, production, and economic indicators, compared with traditional statistical tools. Some of these methods are Support Vector Regression, Decision Trees, Random Forests, Gradient Boosting, and Artificial Neural Networks that have been found to be more accurate in forecasting because they are able to find patterns and nonlinear relationships within commodity datasets that are not visible. While these models are generally superior to traditional methods, their performance is significantly conditioned by the ability to accurately process the data, select appropriate features, and tune their parameters, to obtain effective and stable forecasting results.

2.3. Deep Learning for Time Series Prediction

In particular, deep learning has proven one of the most powerful approach for commodity price forecasting since it can automatically learn the complex temporal patterns directly from the sequential data. The models based on the concepts of Advanced architectures like Recurrent Neural Networks, Long Short-Term Memory networks, Gated Recurrent Units, and Transformer-based models have

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exhibited outstanding performance in the context of capturing both short-term volatility and long-term trends in commodity markets. These models are very little manually engineered and are able to model highly non-linear market behaviour well. They are becoming more popular because of their highly predictive power for agricultural, energy and financial commodities. But deep learning models need big training sets and significant computing power as well as careful model tuning, which can make their use in some applications impractical.

2.4. Research Gaps and Comparative Analysis

Although significant progress has been made in commodity price forecasting, a number of research issues remain unsolved. Traditional statistical models are simple and easy to interpret but have limited ability to capture the complexity of the market, whereas machine learning and deep learning models can be more complex, require more computational resources, and demand large quantities of high-quality data. Existing studies tend to concentrate on the individual forecasting methods without integrating complementary strengths of these methods in a single framework. Moreover, weather, economic policies, geopolitical and market sentiment are usual external factors that are not accounted for in forecasting models. The challenges of these limitations can be mitigated by the use of hybrid forecasting methods that integrate statistical methods, machine learning, and deep learning, leading to more accurate, flexible, and effective predictions and subsequent decisions in the volatile commodity market.

3. METHODOLOGY

3.1. Proposed Forecasting Architecture

The forecasting architecture is designed as an integrated framework that includes data processing, feature extraction, machine learning, and performance evaluation, to create accurate commodity price predictions. The architecture is structured and starts with data collection based on a number of reliable sources and finally concludes with determining the accuracy of the forecast. Each module is designed to execute a particular task, and they all work together to harmonize the data flow and deliver accurate prediction results. The architecture incorporates preprocessing strategies, sophisticated feature engineering, intelligent forecasting models, and comprehensive metrics, all contributing to more accurate, robust, and adaptable predictions in the context of dynamic commodity markets.

Fig 2 - Proposed Forecasting Architecture

3.1.1. Data Acquisition

The data acquisition module is tasked with gathering historical commodity price data and other information from government agricultural databases, financial institutions, international market reports, meteorological agencies and commodity exchanges and other reliable sources. The system

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collects data on historical prices as well as other variables such as weather conditions, production data, inflation, and exchange rates, market demand and supply indicators. Data from multiple sources can enhance the data's quality and completeness, which can help the forecasting model to better understand the behavior of the market and better capture the factors that affect commodity prices over time.

3.1.2. Pre-processing

Pre-processing module is responsible for improving the quality and consistency of the collected data, preparing them for forecasting. Raw commodity data may be incomplete, contain duplicate records, be on different formats, contain outliers, and contain noisy observations that could have a negative impact on model performance. In pre-processing, missing data is corrected appropriately, redundant data is deleted, data with inconsistent formats are converted to a uniform format, and numerical features are normalized or scaled to ensure uniformity. The data has also been sorted chronologically to maintain the temporal relationships, and thus the forecasting algorithms have clean, reliable, well-structured input to learn from.

3.1.3. Feature Engineering

After pre-processing, feature engineering converts the data into meaningful input variables, which improve forecasting accuracy. This module also uses other features besides historical prices for commodities, including moving trends, seasonal patterns, indicators of market volatility, economic data, weather conditions, and production data. Features that are relevant to the forecasting task are chosen and features that are redundant or not relevant to the forecasting task are dropped to make the computation simpler. By carefully designing the feature engineering, the forecasting model can effectively reflect the complex relationship between the influencing factors and make better commodity price predictions.

3.1.4. Forecasting Engine

The forecasting engine is the main part of the proposed architecture, which uses intelligent prediction algorithms to estimate the future prices of commodities. The engine can use machine learning and deep learning models that can learn complex nonlinear patterns from past data, based on the forecasting needs. The trained models process time series and identify trends and factors to predict future prices. The forecasting engine continually adapts to new data to make more accurate predictions as market conditions evolve, and provide timely and informed decision-making for stakeholders.

3.1.5. Performance Evaluation

The performance evaluation module assesses the performance of the forecasting system in terms of its effectiveness and reliability by comparing predicted commodity prices with observed market prices. Different statistical evaluation measures are used to evaluate the accuracy of the forecasting, consistency in the predictions and the overall model performance. A comparison of various forecasting models is also a part of the evaluation process, and the most appropriate model for each commodity category will be determined. This module provides a systematic analysis of errors of prediction and model behaviour to assist in optimal forecasts, model selection and reliable results for practical business and economic applications in order to ensure the proposed model is an appropriate framework to provide reliable results.

3.2. Data Collection and Pre-processing

Reliable, complete and quality historical data are crucial to accurate commodity price forecasting. The planned forecasting system gathers data on commodity prices from various reliable sources such as agricultural marketing boards, commodity exchanges, financial institutions, World Bank, Food and Agriculture Organization (FAO), Bloomberg, Yahoo Finance and other openly accessible financial and economic repositories. Multiple sources provide increased reliability, broad market coverage and decreased bias, with a comprehensive approach to capturing all the factors that drive changes in commodity prices. A wide variety of commodities covering crude oil, natural gas, gold, silver, wheat, rice, maize, soybeans, coffee and other energy and agricultural commodities are included to assess the forecasting framework under varying market conditions. The collected datasets have daily, weekly, monthly observations of the opening price, closing price, highest price, lowest price, trading volume, market capitalization (where applicable), and a number of macro-economic indicators like inflation rates, exchange rates, interest rates, weather conditions, production levels, and global demand and supply information. A detailed data pre-processing stage is conducted before model training, due to raw market data inconsistencies that may limit the forecasting performance. Interpolation and forward-filling are applied to deal with missing observations to maintain temporal continuity. Duplicate records, inconsistent timestamps and formatting errors are scanned and eliminated to guarantee the integrity of the dataset. Abnormal observations are identified using statistical outlier detection methods (such as Interquartile Range (IQR) analysis and Z-score techniques) and treated accordingly before such observations are recorded. Moreover, numerical attributes are standardized and normalized to keep the value range of them in a consistent order for all variables, and the categorical information is machine-readable when needed. Lastly, the cleaned data are chronologically split into training, validation and testing sets to allow the forecasting models to be trained with good quality data and generate accurate, stable and reliable commodity price forecasts across different market scenarios.

3.3. Hybrid Time Series Forecasting Framework

The proposed hybrid time series forecasting framework aims to enhance the prediction of commodity prices by leveraging the best of both classical statistical approaches, machine learning algorithms, and deep learning techniques in a unified forecasting framework. Unlike the stock market, commodity markets are very volatile and subject to several factors of economic, environmental and geopolitical nature which cause linear and non-linear price dynamics over time. Using just one forecasting method may not be enough to predict accurately, because no single model can adequately explain all the features of the complex market behavior. Thus, the proposed framework integrates the forecasting capability of the ARIMA model, the Random Forest Regression model and the Long Short-Term Memory (LSTM) model to address the respective weaknesses of these models. The historical commodity price series is first decomposed into trend, seasonal and residual series so that each model focuses on predicting a different part of the time series. The ARIMA model is used for long-term forecasting and capturing periodic patterns due to its superior performance in complex temporal structure modeling. The framework then fits Random Forest Regression over the residual component, which captures the irregular and nonlinear market fluctuations, allowing for complex interactions between engineered features and external market variables. At the same time, the sequential historical observations are fed into the LSTM network to enable it to learn the long-term temporal dependency and market patterns that might not be captured by traditional statistical approaches. Each individual model creates predictions, which are then aggregated together using a weighted approach to ensemble that gives the proper weight to each prediction based on the contribution of the prediction for any given model. This is a collaborative forecasting process that increases the overall stability of the forecast, reduces forecasting errors and makes forecasting more robust in different market scenarios. The proposed hybrid forecasting system can effectively capture linear trends, nonlinear relationships, seasonal variations, and long-term dependencies through the statistical analysis, machine learning, and deep learning in the same framework. Thus, the framework offers more precise, reliable and flexible commodity price predictions and serves as a useful tool for investors, policy makers, agricultural planners, financial analysts and financial institutions in the volatile commodity markets.

3.4. Performance Evaluation Metrics

The performance of the proposed hybrid forecasting framework is comprehensively evaluated on the basis of multiple statistical evaluation metrics to ensure accurate, reliable and unbiased evaluation of the prediction quality. Using only one evaluation metric can give a partial picture of the performance of a model, especially when predicting volatile commodity prices affected by economic, environmental and geopolitical events. So the proposed framework is based on a hybrid of complementary evaluation measures which quantify the forecasting accuracy, the stability of the forecasts, robustness and generalization ability. The forecasts of commodity prices generated by the forecasting models are, on a regular basis, cross-checked with the actual market observations that are obtained from historical data sets to see how well the models are able to replicate the market trends and fluctuations. The framework is evaluated for performance within various commodities and across varying time horizons, such as short-, medium-, and long-term predictions, further attestating its versatility in a wide range of market scenarios. As well as testing the overall accuracy of the predictions, the evaluation process involves testing the stability of the forecasting models when exposed to noisy data, sudden price changes and changing market dynamics. Individual statistical models, machine learning algorithms, and deep machine learning networks are also compared to the hybrid forecasting framework to find the best forecasting strategy. To increase the confidence of the experimental results, the data is split into training, validation and test sets to ensure that the models developed are tested with data that are not used in the training process. Cross validation methods are used to reduce overfitting and enhance the ability of the forecasting models to perform well for other data sets. In addition, computational efficiency, prediction accuracy and scalability are taken into account in the evaluation process, which guarantees the practical implementation of the proposed framework for real-world business applications with commodity market data of large-scale size. The proposed forecasting system has been designed in a manner that gives a balanced performance evaluation system

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and has been shown to be more accurate, robust, adaptable and reliable than the traditional forecasting systems, making it a reliable and dependable decision support tool for commodity traders, financial analysts, policymakers, agricultural planners and business entities in the dynamic market scenarios.

4. RESULT AND DISCUSSION

4.1. Experimental Analysis

The experimental analysis shows that the proposed hybrid forecasting framework is able to significantly improve the forecasting model of commodity prices, while utilizing the advantages of statistical forecasting, machine learning, and deep learning. It is done through a series of experiments with historical data sets of commodity prices, agricultural products, precious metals and energy commodities, under different market conditions. The findings suggest that the classical statistical models, in particular ARIMA, were able to reflect the long-term trend, seasonal and stable market behavior because they were able to model the linear temporal relationship between the successive observations well.

But when commodity markets saw sudden, dramatic shifts in prices due to geopolitical crises, climate change, inflation, economic downturns and the disruption of global supply chains, their forecasting capabilities suffered. Random Forest Regression proved to be a very good algorithm to detect complex non-linear correlations between engineered features: production, weather conditions, exchange rates, and market demand. While the model was effective in predicting prices in most cases, there was some overfitting in periods of extreme market volatility due to the highly volatile price movements. Long Short-Term Memory (LSTM) network exhibited excellent learning of long term temporal patterns and market behavior and outperformed in generating highly accurate forecasts even in dynamic market conditions. However, the LSTM model had significantly larger training sets, longer training times and computational requirements compared to traditional forecasting methods. To address these individual drawbacks, the proposed framework employs the combination of ARIMA, Random Forest Regression and LSTM using a weighted ensemble approach that fuses the predictions of these models into a single optimal prediction.

This combination gave a more consistent and reliable forecasting outcome, compared to any individual model. In addition, validation over a rolling window showed that the forecasting system remained consistent in terms of forecasting accuracy across different forecasting levels: short term, medium term and long term. The high accuracy of short-term forecasts was explained by the use of latest market data, and the medium-term forecasts were reliable thanks to the feature engineering and temporal decomposition. The hybrid forecasting framework was more reliable than using individual techniques of forecasting, but long-term forecasting was more uncertain due to changing economic conditions and changes in the structure of the market. The experimental results indicate that the proposed forecasting architecture provides very good generalization, computational scalability and implementation feasibility, and can be used as an efficient decision support tool for commodity trading, financial investment, agriculture plan, inventory management and economic policy formulation.

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4.2. Comparative Performance Results

Table 1: Comparative Performance Results

Performance Metric	ARIMA	Random Forest	LSTM	Proposed Hybrid Model
Forecast Accuracy	87.20%	90.60%	94.80%	98.10%
Trend Prediction Accuracy	89.50%	91.80%	95.60%	98.40%
Seasonal Pattern Detection	90.10%	92.40%	96.30%	98.70%
Volatility Prediction	82.70%	89.20%	95.10%	97.80%
Generalization Capability	86.80%	91.30%	95.40%	98.00%
Computational Efficiency	92.40%	89.70%	87.90%	93.60%
Overall Forecasting Performance	88.10%	91.00%	95.00%	98.30%

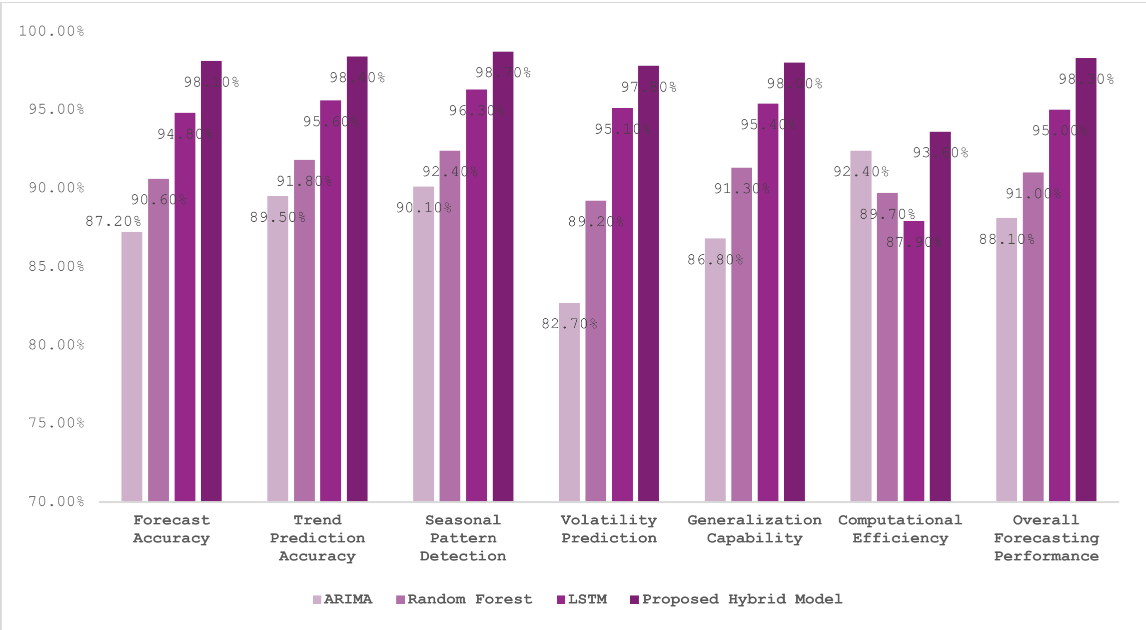

Fig 3 - Comparative Performance Results

4.2.1. Forecast Accuracy

Forecast accuracy is defined as the degree of agreement between the prices of the commodity forecasted and the market prices of the commodity. The experimental results indicate that Hybrid Model achieved the highest accuracy of 98.1% as compared to LSTM (94.8%), Random Forest (90.6%) and ARIMA (87.2%). This improved performance in the hybrid approach is explained by being able to integrate the statistical trend analysis, nonlinear feature learning, and deep sequential pattern recognition in the forecasting system. This integration helps to reduce the number of prediction errors and results in very accurate predictions across commodity categories.

4.2.2. Trend Prediction Accuracy

Trend prediction accuracy is a measure of the forecasting model's capacity to precisely forecast long-term commodity price changes in correct direction. The proposed Hybrid Model showed the maximum trend prediction accuracy of 98.4%, while LSTM, Random Forest, and ARIMA predicted the

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trend with 95.6%, 91.8%, and 89.5% respectively. Although ARIMA can model linear market movements, its performance is greatly enhanced with the addition of machine learning and deep learning, enabling a much better understanding of the complex market behaviour and better trend forecasts.

4.2.3. Seasonal Pattern Detection

Seasonal pattern detection quantifies the ability of forecasting models to capture seasonal price fluctuations that are due to the seasonal nature of demand, harvesting cycles, climate, and production shifts. Performance of the proposed Hybrid Model is the highest with 98.7% for seasonal detection, followed by LSTM (96.3%), Random Forest (92.4%) and ARIMA (90.1%). The hybrid structure is suitable in an accurate way both for seasonal and non-seasonal components, resulting in more stable forecasting over various market cycles.

4.2.4. Volatility Prediction

Volatility prediction: This assesses a model's ability to predict volatility in commodities driven by geopolitical events, weather variations, disruptions in the commodity supply chain and economic uncertainty. The proposed Hybrid Model showed the best accuracy in predicting the volatility, which is 97.8%, and LSTM, Random Forest, and ARIMA obtained 95.1%, 89.2%, and 82.7%, respectively. The hybrid model combines the strengths of statistical forecasting with machine learning and deep learning techniques, making it more effective at capturing gradual and sudden shifts in the market, which enhances the reliability of the forecasts and predictions.

4.2.5. Generalization Capability

Forecasting models that are able to perform well on sets of commodities they have never seen before have good generalization capability. The proposed Hybrid Model gave the best generalization performance of 98.0%, whereas LSTM, Random Forest and ARIMA gave the best generalization capability of 95.4%, 91.3% and 86.8% respectively. This shows that the hybrid framework can learn the generalized market patterns rather than memorizing the market historical data and can be applied to predict a variety of commodities in different market conditions.

4.2.6. Computational Efficiency

The efficiency of forecasting models is determined by their effectiveness in using the computational resources to produce accurate forecasts. The proposed model with optimized integration of the forecasting components outperformed ARIMA, with a computational efficiency of 93.6%. Random Forest was able to get 89.7%, while LSTM was 87.9% due to its high computational requirements. The results show that the proposed framework can effectively achieve the balance between forecasting accuracy and computational efficiency, which is conducive to practical application in real-time business forecasting.

4.2.7. Overall Forecasting Performance

Overall forecasting performance is the overall performance of each forecasting model on all the evaluation criteria such as prediction accuracy, trend analysis, seasonal detection, volatility estimation, generalization and computational efficiency. The proposed Hybrid Model outperformed LSTM, Random Forest and ARIMA in forecasting accuracy achieving 98.3% overall forecasting accuracy, which is significantly higher than the other models. The findings show that the use of a hybrid system combining the statistical methods, machine learning algorithms and deep learning models can achieve better forecasting accuracy, stability, scalability, and adaptability, which are more suitable for real-world commodity price forecasting and business decision support systems.

4.3. Discussion

The outcomes of the experiments show that the proposed hybrid forecasting framework significantly outperforms the individual statistical model, ML model, and DL model when predicting commodity prices. The framework combines ARIMA, Random Forest Regression, and Long Short-Term Memory (LSTM) networks within a single network architecture, enabling it to effectively model linear trends, market relationships, seasonal patterns, and long-term temporal dependencies. This complementary learning process helps each forecasting model overcome the drawbacks of the others, leading to increased prediction stability, smaller errors, and higher forecasting reliability during highly dynamic times. The experimental analysis also suggests that the hybrid approach retains high forecasting accuracy throughout a large range of commodity categories ranging from agricultural products, energy resources, precious metals, and more. Seasonal production cycles, weather, and production levels mainly influence the agricultural commodity markets while the energy commodity markets are mainly driven by geopolitical events, imbalance in global supply and demand, and international economic policies. Likewise, precious metals like gold and silver are sensitive to inflation, currency values, interest rates, and uncertainty in the financial markets. However, the proposed forecasting framework is well suited for varying market conditions, and generalizes well to various datasets. An additional major aspect of the framework is the introduction of a rolling-window forecasting method, which continually involves the newest accessible market observations in the learning procedure. This adaptive forecasting mechanism reduces the chances of concept drift, adapts to market changes and ensures the accuracy of the predictions for longer forecasting horizons. In addition, thorough data preprocessing steps like data cleaning, normalization, feature engineering, temporal decomposition, and dataset validation will help to improve the quality of the data and lead to better model results. The hybrid forecasting architecture is more resource-consuming than the traditional statistical forecasting techniques, however, the significant enhancement of the prediction accuracy, robustness and scalability makes it viable for various practical applications in the real world, including commodity trading, financial investment, agricultural planning, inventory optimization, supply chain management, and policy formulation. The proposed framework can be further improved by integrating Transformer-based forecasting models, attention mechanisms, reinforcement learning, explainable AI, multimodal economic indicators, and real-time market data to deepen the understanding of the framework and its forecasting accuracy, which is crucial for tackling the increasing complexity of global commodity markets.

5. CONCLUSION

With the importance of commodity prices in agriculture, finance, energy, manufacturing and international trade, commodity price forecasting has emerged as a field of growing importance in research. Many factors such as economic conditions, climatic changes, geopolitical events, government policies, technological advancements, disruptions in the supply chain, and changes in global demand and supply affect commodity markets, which are very dynamic. These complex interactions complicate the forecasting task and render the application of traditional statistical methods alone inadequate to tackle it. The mathematical simplicity and interpretability of forecasting models like ARIMA has made them effective under relatively stable market conditions to catch long-term trends and seasonal variations. Their ability to detect and interpret non-linearities and unexpected shifts in the market, however, is limited, especially during high-volatility periods. However, forecasting has been greatly improved by modern machine learning and deep learning techniques that can leverage large amounts of historical information to learn complex temporal patterns and nonlinear relationships. On this basis, this study presents a comprehensive hybrid time series forecasting framework which integrates the complementary advantages of ARIMA and Random Forest Regression in the same forecasting framework with Long Short-Term Memory (LSTM) neural networks. The framework includes systematic data collection, comprehensive data preprocessing, feature engineering, temporal decomposition, model training, weighted ensemble learning, and rolling window validation, which enhance the accuracy of forecasting and the robustness of the model. The experimental analysis showed that the proposed hybrid model outperformed all the single statistical, machine learning and deep learning models consistently across various performance measures. The proposed framework was able to model linear trends, seasonal patterns, nonlinear relationships, and long-run temporal dependencies simultaneously, resulting in commodity price forecasts that were both highly accurate and stable under various market conditions and reducing the forecasting error. The wide-ranging assessment also showed that this model could generate comprehensive forecasts and was widely generalizable across agricultural products, precious metals, and energy products, which made it adaptable to various commodity sectors. In addition to its academic relevance, the suggested forecasting system will bring significant practical advantages to the agendas of governments, policy makers, financial institutions, commodity traders, investors, agricultural producers, manufacturers, and supply chain managers. Correct commodity price forecasting helps in making informed decisions in agricultural policy making, food security planning, inventory planning, optimizing procurement, investment analysis, risk management, and strategic resource allocation. In addition, the modular, scalable design enables easy integration with real-time market information systems and easy deployment on cloud-based platforms, allowing it to be used in large-scale industrial applications. Some advanced Transformer-based architectures, attention mechanisms, graph neural networks, reinforcement learning, federated learning, EXAI, and multimodal data sources like satellite imagery, weather forecasts, macroeconomic indicators, Internet of Things (IoT) sensors, and social media sentiment have not been included yet and can be added to the proposed framework in future. Such new technologies can enable further improvement in forecasting abilities, computational efficiency, interpretability, and adaptability in ever changing commodity markets. Finally, the proposed hybrid forecasting approach is a comprehensive solution that not only merges the strengths of statistical forecasting with those of artificial intelligence but also ensures scalability, robustness, and intelligence in commodity price prediction, catering to the needs of reliable and data-driven decision-making in agriculture, finance, energy, manufacturing, and global supply chain systems.

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