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Multivariate Time-Series Forecasting of Gold Prices Using LSTM Networks

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Abstract- **Gold has a significant impact on the Indian economy and is regarded as an asset for both investment and value storage. Therefore, the creation of the model that moves with time in the pricing of gold is very important for financial planning and risk management. This research offers a multivariate deep learning framework that interconnects global and domestic economic indicators to depict the price of gold in Indian market. The model takes international prices of gold, USD–INR exchange rate, Brent crude oil prices, stock market index, and gold import duty that is considered a policy-driven exogenous variable as well. Long Short-Term Memory neural network is used for its ability to represent nonlinear dependencies and capture the longest period of temporal relationship in data of time-series. The proposed method is tested and compared with traditional statistical models and deep learning baseline methods using standard error metrics.**

Keywords— Gold Price Forecasting, LSTM, Indian Market, Macroeconomic Indicators, Deep Learning

I. Introduction

Gold, in the past, has been the central character of the global money system in the whole world stage, and this was because of its functions as a store of value, an inflation hedge, and a safe haven during difficult times economically and politically. The global factors determining the world over gold prices together with country-specific economic conditions are international gold prices, exchange rates, crude oil prices, interest rates, and stock market movements [18,23,25]. In this regard, for India, gold is a phenomenal asset because of its cultural significance, its heavy demand in households, and its association with savings and investments. Not only does India continue to be a major global importer and consumer of gold but its domestic prices are also very much influenced by changes in the international market and by the overall economic situation [13,20]. To predict gold prices, traditional statistical models like ARIMA and regression-based methods have been the most common ways used so far [9,12]. These methods can capture linear trends and short-term dependencies but in their application to the prediction of gold price they tend to simplify and miss complex nonlinear relationships and long-term temporal dependencies that are usually found in financial time-series data. To mitigate the problems associated with these limitations, recent research has increasingly turned to machine learning and deep learning techniques, particularly Long Short-Term Memory (LSTM) networks, which are ideal for sequential data modeling [19,26]. A few studies have already proved that LSTM and its variations have a clear advantage over classical models when it comes to gold price prediction [2,14,16]. The exchange rate of UDS-INR, prices of brent crude oil, and performance of the stock market (e.g., NIFTY-50 index) are the main ones that determine the mood of the investor and the decisions of asset allocation [10,23]. Import duty changes are commonly employed by the Indian government to resolve trade imbalance and regulate gold imports, which often results in sudden price corrections after the announcement of the policy [7,13].

This study proposes the multivariate model that successfully combines global gold prices, the USD–INR exchange rate, Brent crude oil prices, NIFTY-50 index values, and Indian gold

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import duty into one coherent forecasting system. The study is a proof of concept for the use of deep learning models in capturing structural and policy-related information, which in turn increases their scope of use beyond purely data-driven prediction tasks [1,2,16,19].

Gold serves both economic functions and financial functions, but it also acts as a strategic element for maintaining macroeconomic stability in developing countries. The market depends on external sources which create price instability because international commodity market changes and foreign exchange rates create volatility. The USD–INR exchange rate determines the domestic gold price as it has an impact on gold pricing. Gold prices exhibit a delayed response as their data shows relationships that exist beyond three separate time periods. Traditional time-series models, which typically rely on short memory structures, are ill-equipped to capture such delayed effects. Advanced sequence-learning models which can store past data must be developed because current models lack this functionality.

Existing gold price forecasting studies show that researchers focus on improving predictive accuracy through algorithmic optimization while they fail to study how institutional and regulatory factors affect forecasting results. The existing models maintain their policy-agnostic nature because they operate in markets where government actions control commodity prices. The present study advances the literature by embedding fiscal policy signals within a deep learning framework which enables researchers to move from accuracy-focused modeling to developing economically valuable forecasting systems.

II. Problem Motivation and Need for Policy-Aware Forecasting

The process of forecasting gold prices in emerging economies like India encounters challenges because these countries continue to implement their fiscal policy updates and operate their market control systems. The Indian gold market operates under different conditions from developed markets because government import tariffs and tax regulations and currency exchange rate policies have a major impact on gold prices. The current policy framework creates unexpected price fluctuations which make standard forecasting techniques unusable. Existing predictive models assume that market conditions will remain unchanged while they cannot handle sudden changes that result from new policies. The Indian gold market needs a forecasting system which combines macroeconomic data with fiscal policy information to produce precise market predictions for different market conditions.

III. Literature Review

The fluctuations of gold prices have been continuously researched for the reason gold being a safe-haven asset itself and also for its pivotal position in the economies of both the developed and emerging ones. Initially, the studies tried to identify the causative relationship between gold prices and macroeconomic indicators relying on econometric and statistical methods. A detailed and systematic review of the worldwide gold market was provided by Shafiee and Topal [18]. They pointed out why and how the prices of gold have been affected by economic uncertainty, inflation, and financial instability. The authors' hypothesis, that gold was a hedge and not just a speculation tool, was proved by their work and further studies on gold price forecasting through quantitative methods were inspired by it. Gold prices were looked into by several researchers together with macroeconomic indicators such as exchange rates, crude oil prices, and stock markets. Sujit et al. [23] conducted a study of gold prices, oil prices, exchange rates, and stock market returns, and claimed that gold prices are very sensitive to currency movements and energy prices. Ingalhalli et al. [10] and Tripathy and Tripathy [25] reported similar results; they underlined the strong interconnection between gold, equity, and foreign exchange markets in India. With this, it becomes essential to carry out a multivariate framework for gold price behavior analysis. In India, various empirical studies have pointed to the significance of gold in the domestic economy. Banik [4] explored the relationship between gold prices and exchange rates in India and revealed that both variables influenced each other. Srinivasan and Esakki [22] performed a thematic analysis of the effect of gold prices on the Indian economy, mentioning impacts on trade balance, inflation, and household savings. Narayanaswami [13] pointed out the structural features of the Indian gold trade and the influence of the policy measures in determining gold demand and its price. Gold price prediction has traditionally relied upon forecasting techniques like ARIMA and regression models. Guha and Bandyopadhyay [9] and Makala and Li [12] showcased the potential of ARIMA-based models for short-term gold price evaluation. Yet these models could not overcome the restrictions of not identifying nonlinear patterns and long-term dependencies. Patel [15] and Singh and Kaur [20] echoed the sentiments of the former researchers by stating that the impact of the macroeconomic factors on gold prices is so complex that linear models cannot adequately represent it.

With the upgrading of machine learning techniques, researchers have consequently started using deep learning models increasingly for gold price analysis. Shankar and Reddy [19] did forecast through application of time-series and deep learning algorithms with India as the focus and substantial accuracy increase compared to conventional methods was the outcome. Yurtsever [26] who dealt with LSTM, Bi-LSTM and GRU models and came to the conclusion that recurrent neural networks are better than statistical methods in capturing temporal dependencies. Madhika et al. [11] and Pan [14] confirmed that LSTM-based models are the best among the three. To achieve better forecasting accuracy, recent research has examined hybrid and advanced deep-learning frameworks. Among others, Boongasame et al. [5] suggested an LSTM-based model enriched with association rules while Saini et al. [16] presented a combined LSTM–autoencoder setup for predicting the price of gold. Zangana and Obeyd [27] also

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proved that deep learning models are mainly useful when the market is going through volatile conditions. The findings of comparative studies by Ahmad et al. [1] and Aljohani et al. [2] also imply that deep learning methods are decisively superior to classical statistical methods across all evaluation metrics. A lot of research has been carried out on gold price forecasting using macroeconomic and financial indicators, but not many studies have looked directly into the relationship between fiscal and policy interventions and gold prices. Emmanuel [7] studied Indian gold policies and reforms and pointed out that the import regulation and duty structure are among the factors that have a high impact on the import of gold and its domestic consumption pattern. Nevertheless, these kinds of studies are mostly qualitative and are not usually used in predictive modeling frameworks. Narayanaswami [13] pointed out that the Indian gold market is, in fact, different from global markets structurally because of the heavy policy intervention, mainly through import duties and regulatory controls. The authors claim that the domestic price variations cannot purely be accounted for by the global price and exchange rate variations. Singh and Joshi [21] confirm this observation by indicating that the economic and policy conditions in India significantly affect gold's role as an inflation hedge. To these deductions, the majority of the forecasting models give precedence to international variables only. Numerous empirical investigations have investigated the influence of macroeconomic shocks on gold prices but did not cover the analysis of discrete policy events. Arora et al. [3] and Ingalhalli et al. [10] provided evidence of the interconnection between oil, stock, forex, and gold markets, revealing that gold prices are not only sensitive to but also show a disproportionate response to market volatility. Nevertheless, the studies have regarded changes in policy as implicit background factors rather than explicitly articulating them as informing variables. A parallel case is Takhre and Pimplapure [24] that investigated the relationship among the prices of crude oil, equities, and gold but did not include government policies such as import duties or taxation changes as influencing factors. The most recent comparative studies have been directed towards the assessment of the predictive accuracy of various modeling techniques. Ahmad et al. [1] and Pan [14] were among those who scrutinized machine learning and deep learning models along with the conclusion that LSTM-based methods always surpass traditional statistical models. Aljohani et al. [2] even more confirmed the idea of superiority of multivariate deep learning frameworks in comparison with univariate models. However, these studies predominantly assess the model's performance in terms of accuracy of metrics and do not evaluate the interpretability or policy sensitivity of the models. One more major restriction present in literature is the non-utilization of events for validation in most cases. It is the total error measures that such as RMSE or MAE are widely used for the evaluation of forecasting models in terms of their performance, without putting the models to test on how market sudden changes influence them. Authors Shankar and Reddy [19] and Saini et al. [16] indicate the models' high predictive accuracy under normal circumstances but do not test the models' capabilities during times of policy shocks or regulatory interventions. This leads to the situation where it is not clear whether the current models are the ones that can cope with fluctuations in the real-world fiscal scenario.

Current research clearly shows that deep learning methods achieve better predictive results than traditional econometric models yet most studies focus on comparing research methods instead of applying them to real economic situations. The existing studies assess model performance through statistical accuracy standards yet they fail to include policy variables which can explain fundamental market shifts. The existing research fails to establish models which can handle both economic linkages and regulatory impacts especially in the Indian gold market.

IV. METHODOLOGY

The process of feature selection needs to use two standards which include economic relevance and previous study empirical evidence. The multivariate input structure enables the model to acquire knowledge about how different variables interact with each other throughout different time periods. The LSTM model uses sequential historical data for training as this data helps the model understand short-term changes and long-term patterns.

A. Data Collection

Yahoo Finance serves as a trusted financial data provider from which we obtained global gold prices and USD–INR exchange rates and Brent crude oil prices and the NIFTY 50 stock market index. International markets use global gold prices as their standard gold valuation, which shows that USD–INR exchange rate movements directly determine the domestic cost of imported gold. The study utilizes Brent crude oil prices to show how global economic conditions and inflationary pressures affect the economy while the NIFTY 50 index shows how the domestic stock market performs and how investors feel about the market. The dataset follows a daily frequency that permits the system to identify both tiny price fluctuations and short-term gold price movements together with their related macroeconomic information. The data collection covers the time frame from January 2015 until December 2025 which allows researchers to study various market behaviors during both unstable times and periods of governmental change. The system uses this time frame to learn about both established market trends and dynamic shifts in market behavior.

B. Data Pre-processing

The gathered data required thorough preprocessing work before model training because this process improved data quality and made the data suitable for time-series analysis. The data contained inconsistencies because it was collected from multiple sources which resulted in missing values that occurred during holidays and during times when data was not reported. The researchers used interpolation and forward-fill methods to

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bridge the gaps which allowed them to maintain the series natural progression while maintaining continuity throughout the process. There is conversion of all variables into a standard daily schedule which enables to achieve proper feature synchronization throughout the study. The system applied Min-Max normalization as a feature scaling method which transformed all input data into a designated limited range. This step helps to maintain stability during neural network training while it prevents any single factor from dominating the process because of varying measurement scales. The model preprocessing stage plays a crucial role in enhancing both model performance and model trustworthiness.

C. Feature Engineering

The research developed lagged input variables which enabled researchers to study the time-dependent relationships between gold price movements. The model uses lagged features to discover how economic and policy variables from the past effect future gold price movements. The model needs to represent these import duty changes because they cause sudden shifts in domestic gold prices which result from marketable goods price changes. The research created features which show how global market conditions.

D. Model Development

Long Short-Term Memory (LSTM) neural network was used because it can easily handle both sequential data and nonlinear financial time-series data. Its function works effectively in situations which require them to maintain essential past data throughout extended time durations. The model learned through historical data so that it can identify complicated connections between gold prices and the chosen macroeconomic and fiscal factors.

E. Model Architecture

The LSTM model consists of memory cells equipped with gating mechanisms that regulate the flow of information. The system uses gates for maintaining the essential past data while throwing away useless information. The design improves model performance during market fluctuations and sudden policy changes, which helps it predict gold prices in India, a market that operates under strict regulations and governmental policies. The proposed model consists of a stacked architecture with two LSTM layers with 64 units and connect to a fully connected dense layer that produces the final output. The system includes a dropout layer which links two LSTM layers to decrease overfitting while increasing model ability to generalize. The model uses sliding time windows to handle sequential input data because this method allows it to detect short-term changes and long-term patterns in financial time-series data.

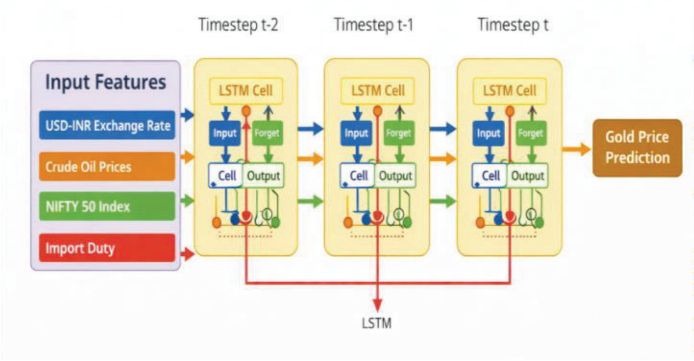

Fig. 1. LSTM Architecture

F. Training Configuration and Model Design Transparency

The Long Short-Term Memory network uses a learning system which trains through supervised methods to predict multiple streams of time-dependent data. The system applied delayed input variable observations to create a model that simulated both postponed economic effects and chronological connections. The Adam optimizer served to optimize model parameters while Mean Squared Error (MSE) functioned as the training loss function to minimize prediction errors. The final setup creates a model design which sustains accurate predictions through its combination of advanced model components and fundamental elements. There is implementation of structured hyperparameter tuning methods which led to improved model stability. There is examination of different network size configurations and input sequence length parameters together with various training settings to find the best combination. The study evaluated different combinations of parameters while using validation performance as the selection method instead of using fixed values. The process enabled better prediction results because it prevented problems which cause overfitting and underfitting. There is selection of final model settings based on their ability to handle new data which remained unseen instead of their performance in training dataset evaluation.

G. Model Evaluation

The study used Root Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE) because these metrics provide both absolute error and relative forecasting error measurement. RMSE method detects main prediction errors through its penalty system which imposes greater penalties for significant prediction mistakes. MAPE method provides a standardized error assessment which enables users to understand pricing data throughout different pricing situations. The model performance assessment included R-squared (R^2) and Mean Bias Error (MBE) in addition to the three measurement methods of RMSE, MAE, and MAPE. The R^2 metric measures the proportion of variance in gold prices explained by the model which allows assessment of model accuracy. The model performance evaluation uses MBE to measure systematic prediction bias because it shows whether the model tends to predict higher or lower than actual values.

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The additional metrics provide a complete evaluation system which assesses forecasting accuracy.

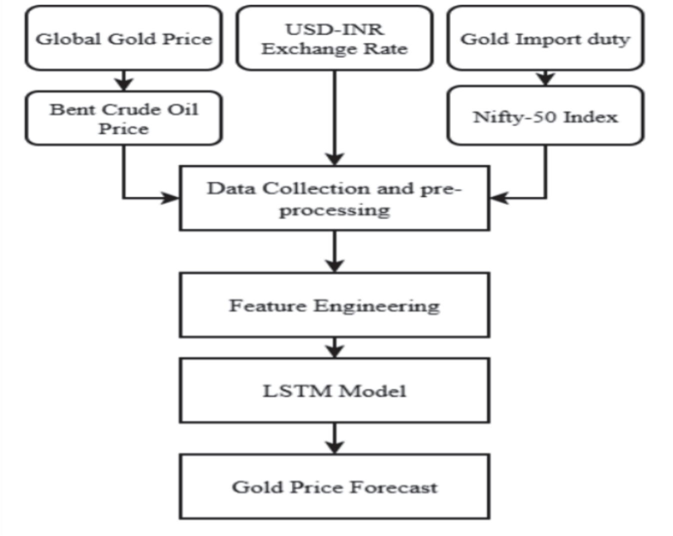

Fig. 2. Methodology Flow Diagram

V. RESULTS AND FINDINGS

The evaluation results pointed out that the LSTM model managed to not only detect short-term fluctuations but also the long-range price trends in gold. The forecast values were in tight proximity with the actual gold price movements, thus allowing the model to be termed as one that has the capability to extract complex temporal patterns which are typical of financial time series data. The model shows improvement during periods of high volatility because it can adjust to different market conditions which arise from policy announcements.

The observed improvement in forecasting performance results from both model complexity and the inclusion of economically significant explanatory variables. Exchange rate movements determine import costs and investor hedging practices while crude oil prices function as indicators of global inflationary pressure and macroeconomic uncertainty. The proposed framework learns economic connections to capture both statistical patterns and structural market dynamics.

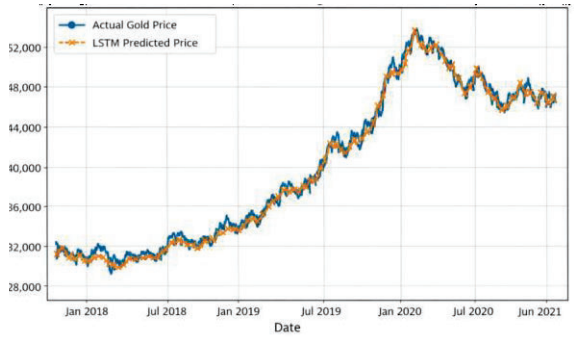

Fig. 3. Comparison of Actual and Predicted gold price

The standard regression metrics, which include Mean Absolute Error, Root Mean Squared Error and Mean Absolute Percentage Error allowed for a quantitative evaluation showing that the proposed model was very low in prediction errors throughout the testing period. These findings underline the model as a source of reliable and correct forecasts that are even acceptable for practical financial decision-making. The extended evaluation metrics confirmed that the proposed model showed strong performance across multiple testing methods. The high R^2 value demonstrated strong explanatory power, and the near-zero MBE value showed minimal prediction bias. The results of this study validate the multivariate LSTM framework as a reliable tool for financial forecasting in real-world applications.

A comparison in the form of analysis was made by placing LSTM model alongside conventional forecasting methods of ARIMA and basic regression models and then evaluating the former against the latter. The results clearly demonstrate that the LSTM-based model outperformed the baseline methods in all evaluation metrics. Through a detailed examination of the model's performance, it was revealed that the forecasting accuracy was significantly enhanced by the input of several macroeconomic variables. The Indian rupee to US dollar exchange rate and the NIFTY-50 index were among the factors that made the model more responsive during times of change in the currency and the stock market. Likewise, the factor of crude oil prices being included in the model helped to perceive the inflation and the global economic conditions that, in a way, are controlling the price of gold. This clearly shows the superiority of a multivariate method to the univariate price-based models.

VI. CONCLUSION AND FUTURE SCOPE

This research work has introduced a multivariate deep learning architecture for predicting gold prices in the Indian market that combined global commodity indicators with domestic macroeconomic variables. The proposed model utilized a Long Short-Term Memory (LSTM) network that works well in capturing nonlinear relationships and long-term temporal dependencies which are already embedded in the financial time series data. The different experiments' results indicated that the LSTM-based approach had a clear advantage over traditional

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methods such as ARIMA and simple regression particularly during stressful market periods. The addition of various explanatory factors which included global gold prices, USD-INR exchange rates, Brent crude oil prices, and the NIFTY-50 index among others made the prediction of the model more accurate and robust. The conclusions from this study are that it is crucial to have a multivariate as well as market-aware modeling approach for gold price prediction in the case of emerging economies especially India. The proposed framework incorporates significant economic variables and reveals global trends, currency changes, energy market position, and investor mood, which are not only the basis for historical price data but also univariate models. Thus, the model offers more realistic and reliable predictions that go hand in hand with real market behavior. This could lead to better decisions being made by investors, financial analysts, and policymakers who are dealing with gold investments and risk management. The study was strong but had limitations, which are the foundations of future research. One of the limitations was the current model which relied on a restricted range of macroeconomic indicators while not taking fully into account the micro-factors that influence customer demand and speculative trading activities. Furthermore, even though the LSTM architecture is excellent for modeling time-based relations, it may completely miss the rapid changes in structure due to sudden geopolitical events or policy shifts. Improvements in these areas could still yield greater forecasting accuracy, model interpretability, and so on.

Future studies will likely have many different paths based on the present work. One way would be to consider 'Bidirectional LSTM, Gated Recurrent Units (GRU), or attention-based Transformer models' as deep learning forms of an advanced level, which possess a greater predictive capability. Furthermore, the researchers may take the knowledge of gold price dynamics more extensively by considering the variables such as interest rates, inflation indices, or even sentiment indicators generated through news and social media, which are more comprehensive than the existing ones. Moreover, multi-horizon forecasting or adapting the proposed framework for use in other commodities and emerging markets would be further avenues of application for the model.

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