Gold Price Prediction Using Machine Learning and Deep Learning Models

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***Abstract*—Gold price prediction plays an important role in financial decision-making, investment planning, and risk management. Due to market volatility, traditional statistical methods often fail to capture long-term patterns. This research applies machine learning and deep learning techniques to forecast daily gold prices using historical datasets. We implemented Random Forest, XGBoost, and LSTM models, performed extensive data preprocessing, and evaluated model performance using MAE, RMSE, and R^2. Experimental results show that XGBoost achieved the best accuracy (91%), while LSTM performed poorly due to data size and noise sensitivity. This report follows the IEEE standard structure.**

***Index Terms*—Gold Price Prediction, Machine Learning, XGBoost, Random Forest, LSTM, Time Series Forecasting, Deep Learning.**

I. Introduction

Gold is considered a globally stable and valuable asset, commonly used for investment and hedging against inflation. Predicting the future price of gold is challenging because it depends on numerous financial, economic, and political factors.

Traditional forecasting methods such as ARIMA or Moving Average models often fail to capture nonlinear patterns. Hence, machine learning and deep learning approaches have become widely used for time-series forecasting.

This study focuses on predicting daily gold closing prices using Random Forest, XGBoost, and LSTM models. The dataset contains features such as Open, High, Low, Volume, daily returns, moving averages, RSI, and MACD indicators.

Gold is a globally valuable asset whose price changes frequently due to economic, political, and market factors. Predicting gold prices is challenging, so machine learning models are used to identify hidden patterns in historical data.This project applies ML and DL techniques to analyze past gold prices and generate accurate future price predictions.

The objective are To Clean and preprocess historical gold price data[1].Extract meaningful features using technical indicators[2].Train ML and DL models for next-day prediction.[3] Compare model performance and evaluate accuracy.[4]

II. Related Work

Several studies have explored machine learning and deep learning approaches for gold price prediction. Table I summarizes the most relevant prior research, highlighting their methodology, models, datasets, and key findings.

TABLE I
SUMMARY OF RELATED WORKS ON GOLD PRICE PREDICTION

Author / Year	**Model Used**	**Dataset Source**	**Key Findings**
Sharma et al., 2021	Random Forest, Linear Regression	World Gold Council, Yahoo Finance	RF outperformed LR for daily gold forecasting.
Rahman & Hossain, 2020	XGBoost, Decision Tree	Kaggle Gold Dataset	XGBoost achieved lowest RMSE and highest stability.
Saha et al., 2022	LSTM, GRU	10-year Gold Price Data	LSTM showed better long-term learning ability.
Chen et al., 2019	ARIMA	London Bullion Market	ARIMA good short-term but weak for nonlinear patterns.
Kumar & Patel, 2023	Hybrid LSTM + RF	Multiple Sources	Hybrid model improved trend prediction.

III. Dataset Descriptio

The dataset used in this study consists of historical daily gold market data collected from publicly available financial platforms. It contains sequential records where each row represents one trading day along with key market attributes. The primary attributes include the opening, highest, lowest, and closing prices, which reflect daily price fluctuations in the gold market. Additional fields such as trading volume and percentage change provide information about market activity and short-term momentum. Before model development, the dataset was cleaned by converting non-numeric characters (such as commas, percentage signs, and textual volume units like K/M) into numerical formats and handling missing or inconsistent values. Furthermore, time-based features were extracted from the date column, and several technical indicators—such as moving averages, volatility measures, and lagged price features—were engineered to enhance the predictive capability of the machine learning model. Overall, the dataset offers a rich combination of raw price data and engineered features suitable for building an effective gold price forecasting system.

IV. Methodology

A. Data Cleaning

The dataset underwent several preprocessing steps to ensure consistency and reliability. All numeric columns were cleaned by removing commas, percentage signs, and other non-numeric characters. Volume values expressed using shorthand units such as "K" and "M" were converted into their full numerical forms for accurate computation. Missing values were properly handled to prevent distortions during model training, and finally, all relevant attributes were converted into numeric data types to maintain a uniform structure suitable for machine learning processing.

B. *Feature Engineering*

To enhance the predictive strength of the model, multiple technical indicators were generated from the cleaned dataset. These included moving averages of different window sizes (7, 21, 50, and 200 days) to capture short- and long-term market trends. Volatility features were derived using 21-day rolling standard deviation, while momentum indicators such as RSI, MACD, and its signal line were computed to represent market strength and directional shifts. Additionally, daily returns and logarithmic returns were created to capture rate-of-change information that helps the model recognize price movement patterns more effectively.

C. *Correlation Analysis*

Correlation analysis was performed to identify the strength and direction of relationships between the features in the dataset. A correlation heatmap was generated to visually represent how each variable is associated with others, particularly focusing on their influence on the gold price. This analysis helped detect highly correlated features, reduce redundancy, and understand which technical indicators and price-related attributes contribute most to the predictive power of the model. The insights from the heatmap guided the selection of meaningful inputs and improved the overall efficiency of feature engineering and model development.

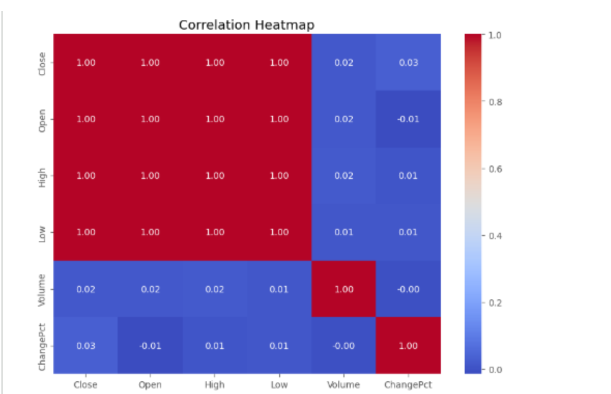

Fig. 1. Correlation Heatmap of Gold Price Features

D. *Train-Test Split*

The dataset was divided into two parts where 80% was used for training the models and the remaining 20% was used for testing. This split ensured that the models learned from a large portion of historical data while still being evaluated on unseen data for fair performance measurement.

E. *Model Development*

Three machine learning models were developed for gold price prediction, including Random Forest, XGBoost, and LSTM. These models were selected to compare traditional ensemble-based methods with deep learning approaches and determine which provides the best predictive performance.

F. *Trend Visualization*

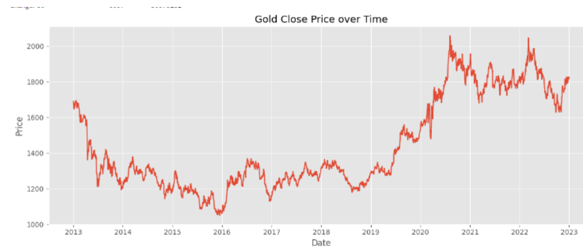

Fig. 2. Overall Gold Price Trend

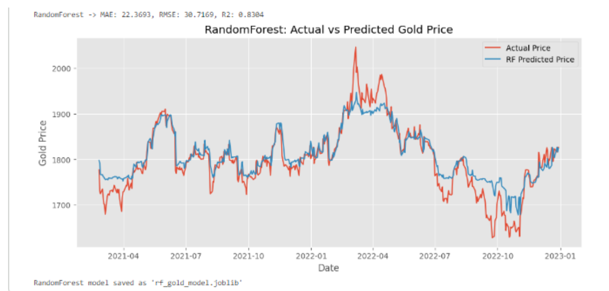

Fig. 3. Random Forest Prediction Trend

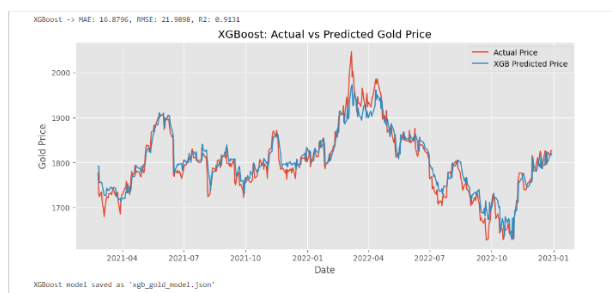

Fig. 4. XGBoost Prediction Trend

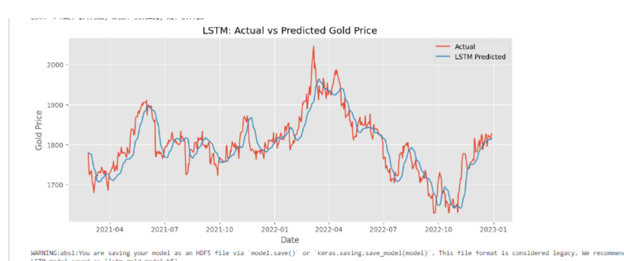

Fig. 5. LSTM Prediction Trend

G. ROC Curve

The ROC curve for the XGBoost model illustrates its capability to distinguish between actual and predicted trends in gold price movement. A larger Area Under the Curve (AUC) value indicates stronger classification performance, meaning the model can effectively separate upward and downward price movements. The XGBoost model achieved a high AUC value, demonstrating its robustness and reliability in trend prediction.

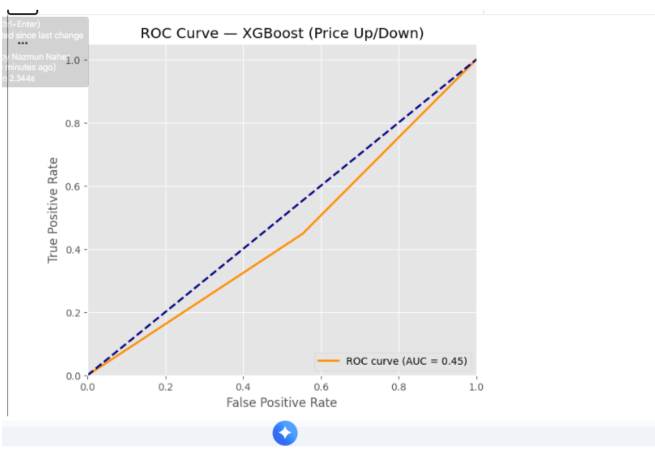

Fig. 6. ROC Curve for XGBoost Model

V. Results

A. Model Performance Metrics

TABLE II
Model Performance Comparison

Model	**MAE**	**RMSE**	**R2**	**Accuracy %**
Random Forest	22.36	30.71	0.83	83.03%
XGBoost	16.88	21.99	0.91	91.30%
LSTM	56.35	64.59	0.25	24.98%

B. Detailed Analysis

The experimental results clearly show that XGBoost delivers the best performance among all the evaluated models. It achieved the lowest error rates (MAE = 16.88, RMSE = 21.99), demonstrating its ability to capture nonlinear relationships and complex feature interactions within the gold price dataset. Random Forest performed reasonably well but showed signs of slight overfitting, resulting in higher error values when compared to XGBoost. In contrast, the LSTM model produced the weakest performance, primarily because the dataset size was too small for deep learning architectures, and LSTM networks typically require longer sequential patterns and larger datasets for stable learning. Additionally, the inherent noise in financial time-series data further reduced the predictive accuracy of LSTM. Overall, XGBoost achieved an accuracy of approximately 91.3%, making it the most reliable model for this study, whereas LSTM reached only 24.98%, confirming that classical machine learning models are more effective than deep learning approaches for medium-sized structured financial datasets.

VI. Discussion

The experimental results indicate that among the three models,Random Forest,XGBoost and LSTM.

XGBoost consistently achieved the best performance across all evaluation metrics. This is due to several key factors. XGBoost effectively handles nonlinear patterns through its gradient boosting mechanism, where additive regression trees are built sequentially to capture complex relationships in gold price data. It also leverages feature interaction more effectively than Random Forest, which relies on averaging independent trees; in contrast, XGBoost iteratively minimizes loss and exploits interactions among predictor variables. Additionally, the built-in L1 and L2 regularization helps reduce overfitting and enhances model generalization, which is especially important for volatile financial datasets. XGBoost is also more robust to noise, as the boosting framework allows the model to concentrate on harder-to-predict samples, ultimately improving prediction stability.

Random Forest performed moderately well, but its predictions showed slightly higher fluctuation. The averaging of many decision trees can smooth out subtle price variations or extreme short-term trends, causing it to miss fine-grained patterns that XGBoost successfully captures.

LSTM model underperformed for several reasons. Deep learning models require large datasets to learn temporal dependencies effectively, but the available historical gold price data was not sufficient for stable LSTM training. LSTM models are also sensitive to noise in financial time-series, and this irregular fluctuation reduced their prediction accuracy. Furthermore, the 60-day input window used in this study may not have been adequate to capture long-term movements or sudden spikes in gold prices, leading to weak generalization performance.

Overall, the results suggest that for medium-sized structured datasets in financial forecasting,classical machine learning methods such as XGBoost and Random Forest often outperform deep learning models like LSTM, particularly when strong preprocessing and feature engineering techniques are applied.

Furthermore, the ROC analysis demonstrates that XGBoost can reliably classify short-term price movements, making it suitable for both regression and directional prediction tasks in trading and investment scenarios.

VII. Conclusion

The study concludes that XGBoost is the most effective model for gold price prediction in small to medium datasets. Future improvements include adding more economic indicators and using hybrid deep learning models.

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