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Hybrid Evolutionary-Optimized Deep Learning Model (Heodl) For Gold Price Prediction

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ARTICLE INFO	ABSTRACT

Gold serves as a hedge against inflation and economic uncertainty, making it a crucial duty in financial markets to predict gold prices. Since gold price changes are complicated, nonlinear, and volatile, traditional forecasting models frequently have difficulty keeping up. We present the Hybrid Evolutionary-Optimized Deep Learning (HEODL) model, which combines Random Forest Feature Selection (RF-FS) for dimensionality reduction, Differential Evolution (DE) for hyperparameter optimization, and Long Short-Term Memory (LSTM) networks for sequential learning in order to overcome these difficulties. Techniques from Explainable AI (SHAP) are also used to improve the interpretability and transparency of the model. The results show that the HEODL model achieves greater accuracy in gold price forecasting, outperforming baseline models like ARIMA, conventional LSTM, and Random Forest. The use of explainability approaches also enables a better understanding of the primary economic variables influencing variations in the price of gold, making HEODL a useful tool for financial analysts, investors, and policymakers.

Keywords: Random Forest, Long Short-Term Memory, Differential Evolution, Hybrid Evolutionary-Optimized Deep Learning, and Gold Price Prediction.

1. Introduction

One of the most expensive assets on the international financial market, gold is frequently utilized as a hedge against economic instability and inflation. Predicting gold prices is a complicated process because to the interplay of various factors such as currency changes, interest rates, inflation, and global economic policies (Beena & Durgadevi, 2024). Because financial markets are very volatile and non-linear, traditional statistical methods have had difficulty producing reliable forecasts. Consequently, methods for data mining and machine learning have become useful instruments for raising forecast accuracy.

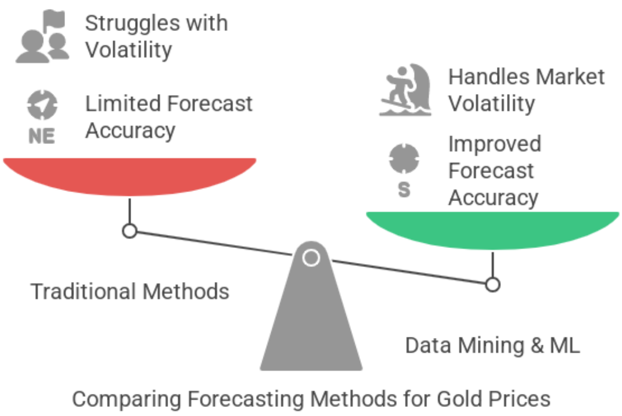

Figure 1. Comparing Forecasting Methods for Gold Prices

Gold price forecasting has demonstrated encouraging results using machine learning models as Support Vector Machines (SVM), Random Forest (RF), Artificial Neural Networks (ANNs), and Long Short-Term Memory (LSTM) networks (Tan &Gabud, 2024). While deep learning techniques like LSTM have shown higher performance in handling time-series predictions, SVM and RF models are frequently employed because of their capacity to identify patterns in financial data (Zhang et al., 2025).
Convolutional Neural Networks (CNNs) and LSTM have been used in recent research to create hybrid models that improve predicted accuracy by capturing both temporal and spatial data (Putri et al., 2025). Furthermore, machine learning frameworks increasingly incorporate optimization methods like Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) to improve predictions and lower mistakes (Kumar et al., 2024).
The combination of deep learning and hybrid models has transformed gold price predictions with the ongoing development of artificial intelligence, giving investors and financial experts more trustworthy information (Abbasi et al., 2024). The accuracy and resilience of gold price prediction models have greatly increased due to the growing availability of real-time financial data and developments in machine learning (Chiu et al., 2024).

2. Literature Survey

Support Vector Machines (SVM) and Long Short-Term Memory (LSTM) networks were compared by Lakshminarayanan and McCrae (2019) for predicting the prices of stocks and commodities, including gold. According to their research, LSTM performed noticeably better than SVM because it could identify long-term dependencies in time-series data, which made it a better option for predicting financial patterns.

Support Vector Regression (SVR), LSTM, and Artificial Neural Networks (ANNs) were investigated by Yang and De Montigny (2022) for gold price prediction. According to their findings, ANN and LSTM outperformed SVR in terms of prediction accuracy. Because LSTM can successfully handle sequential dependencies, it showed particularly good results.
In order to anticipate gold prices, Mithu et al. (2021) looked into the use of Random Forest Regression, Support Vector Regression (SVR), and Adaptive Neural Fuzzy Inference System (ANFIS). According to their research, Random Forest's ensemble learning strategy allowed it to beat other models and attain the highest accuracy (99.57%).

For the purpose of predicting the price of gold, Livieris et al. (2020) created a hybrid Convolutional Neural Network (CNN) and LSTM model. According to their research, LSTM captures long-term dependencies and CNN efficiently pulls significant features from previous pricing data, making this model extremely useful in enhancing predicting accuracy.
In order to estimate gold prices, Cohen and Aiche (2023) examined Random Forest, SVM, and Neural Networks. According to their research, SVM performed poorly when dealing with complex and non-linear financial data patterns, but Random Forest and Neural Networks produced the best accurate predictions.
In order to predict gold prices, Liang et al. (2022) developed a hybrid LSTM-CNN-CBAM model that combines Convolutional Neural Networks (CNN), Convolutional Block Attention Mechanism (CBAM), and Long Short-Term Memory (LSTM). Their findings showed a notable increase in prediction accuracy when compared to conventional machine learning methods.
TP and Sultana (2024) evaluated a number of machine learning models for gold price predictions, including Random Forest, AdaBoost, SVM, Linear Regression, and Neural Networks. According to their findings, Random Forest's capacity to capture intricate feature interactions allowed it to surpass other models in terms of predicted accuracy.

3. Research Methodology

The high level of financial market volatility and the impact of numerous external factors, like inflation, interest rates, and geopolitical events, make it difficult to predict the price of gold. The Hybrid Evolutionary-Optimized Deep Learning (HEODL) model combines Random Forest Feature Selection (RF-FS), Differential Evolution (DE), and Long Short-Term Memory (LSTM) to increase prediction resilience and accuracy. Furthermore, financial experts can understand and interpret the model with the use of Explainable AI (XAI) tools like SHAP.

3.1 Dataset Collection

The New York Mercantile Exchange (NYMEX) publishes historical gold price data in the Yahoo Finance Gold Futures Dataset. Predicting the price of gold is one of the many machine learning and financial analysis uses for this dataset.

Description:

- The dataset contains gold price data on a daily, weekly, or monthly basis.
- It displays trade volume in addition to open, high, low, close, and adjusted closing prices.

- The time-series format of the data makes it perfect for price predictions using machine learning models like LSTMs, Random Forest, and SVM.

Dataset Attributes and Features:

Feature	Description
Date	The date of gold price recording.
Open Price	The price at which gold started trading on that day.
High Price	The highest price of gold reached during the session.
Low Price	The lowest price of gold recorded in the session.
Close Price	The final price of gold at market close.
Adjusted Close	Price adjusted for corporate actions such as dividends and stock splits.
Volume	The number of gold futures contracts traded on that day.

Table 1. Dataset Attributes and Feature Descriptions

The Hybrid Evolutionary-Optimized Deep Learning (HEODL) model has the following steps:

Step 1: Data Collection & Preprocessing

1. Gather historical gold price information from websites such as Kaggle, LBMA, or Yahoo Finance.
2. Retrieve economic information, such as interest rates, crude oil prices, the USD index, and the inflation rate.
3. Use interpolation or mean imputation to deal with missing values.
4. Apply Min-Max scaling to the dataset to normalize it:

$$X' = \frac{X - X_{min}}{X_{max} - X_{min}}$$

5. Divide the dataset into sets for testing (20%) and training (80%).

Step 2: Feature Selection Using Random Forest (RF-FS)

Interest rates, currency exchange rates, inflation, stock market indices, and crude oil prices are some of the variables that affect changes in the price of gold. All of these elements do not, however, have an equal impact on price changes. Due to overfitting, adding extra features might lengthen computation times and decrease model accuracy.The most crucial features are found using Random Forest Feature Selection (RF-FS) in order to address this. The procedure entails:

1. A Random Forest model is trained with the historical gold price information.
2. Determining the significance of each feature by estimating its contribution to prediction error reduction.
3. Cutting out extraneous inputs and choosing only the most important features.

Gold prices are determined by Random Forest (RF), which chooses the most significant economic variables.

1. Run the dataset through a Random Forest model.
2. Compute Feature Importance(I_j) using Gini Impurity:

$$I_j = \sum_{t \in T} p_t(1 - p_t)$$

where p_t is the proportion of class samples in node t .

3. Select topN features based on importance scores.

These features are passed to LSTM for training.This stage increases the accuracy and efficiency of the model by ensuring that only highly significant economic indicators are used as inputs.

Step 3: LSTM Model for Time-Series Forecasting

Gold price predictions is a good fit for LSTM, a deep learning model created especially for managing sequential data. By remembering long-term dependencies, LSTM avoids the vanishing gradient issue that plagues conventional recurrent neural networks (RNNs), in contrast to typical neural networks.There are three primary gates in the LSTM network:

1. Forget Gate: Decides which historical data ought to be deleted.
2. Input Gate: Decides what new information should be added to the cell state.
3. Output Gate: Selects relevant information to be passed to the next time step.

Data on the price of gold and economic indices (such the USD index, inflation rate, and oil prices) are fed into the LSTM network in this model. The output is the anticipated price of gold in the future. Using historical data, the LSTM is taught to identify trends in economic conditions and price changes.

1. Forget Gate(decides what information to discard):

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f)$$

where:

- f_t = forget gate output
- W_f = weight matrix
- h_{t-1} = previous hidden state

- x_t = current input
- b_f = bias
- σ = sigmoid activation function

2. Input Gate (decides what new information to store):

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$
$$\widetilde{C_t} = \tanh(W_C \cdot [h_{t-\mathbf{1}}, x_t] + b_C)$$
$$C_t = f_t \cdot C_{t-\mathbf{1}} + i_t \cdot \widetilde{C_t}$$

where C_t is the updated cell state.

3. Output Gate(decides what the next hidden state should be):

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o)$$
$$h_t = o_t \cdot tanh(C_t)$$

where $h_t$is the final hidden state.The LSTM model predicts gold price(y_t) using:

$$y_t = f(h_t)$$

where f is a dense output layer with linear activation.

Step 4: Hyperparameter Optimization Using Differential Evolution (DE)

The learning rate, number of hidden units, dropout rate, and batch size are among the ideal hyperparameters that must be chosen when training a deep learning model. Inadequate generalization or overfitting may arise from poorly selected hyperparameters. To get around this, the hyperparameter tuning procedure is automated using Differential Evolution (DE).

DE is an evolutionary optimization algorithm that works by:

1. Generating an initial population of random hyperparameter values.
2. Applying mutation and crossover to create new candidate solutions by combining the best-performing parameters.
3. Selecting the best candidates based on the model's performance (measured using Mean Absolute Percentage Error (MAPE) or Root Mean Square Error (RMSE)).
4. Repeating the process until the best set of hyperparameters is found.

DE Algorithm Steps

1. Initialize a populationof solutions (random hyperparameters).

2. Mutation (create new candidates by combining existing solutions):

$$V_i = X_{r1} + F \times (X_{r2} - X_{r3})$$

where:

- V_i = *mutant vector*
- X_{r1}, X_{r2}, X_{r3} = *random parameter vectors*
- F = *mutation factor (scaling parameter)*

3. Crossover (combine mutant vector and existing parameters):

$$U_i = \begin{cases} V_i, if\, r_j < C_r \\ X_i,\ otherwise \end{cases}$$

where C_r is the crossover probability.

4. Selection (choose the best candidate):

$$X_i = \begin{cases} U_i,\ \boldsymbol{if}\ f(U_i) < f(X_i) \\ X_i,\ otherwise \end{cases}$$

where $\boldsymbol{f(X)}$is the model error (MAPE or RMSE).

The best set of hyperparameters from DE is used to fine-tune LSTM.By integrating DE with LSTM, the model automatically selects optimal hyperparameters, leading to better prediction accuracy and stability.

Step 5: Explainability Using SHAP

As "black boxes," deep learning models are difficult to read, making it hard to comprehend why a certain prediction was produced. This is one of its main disadvantages. In order to tackle this issue, the HEODL model integrates Explainable AI (XAI) methodologies like SHAP (SHapley Additive exPlanations).

- SHAP values measure the contribution of each feature (e.g., inflation rate, oil prices) to the final gold price prediction. This allows financial analysts to see which economic factors have the most impact on gold price movements.

SHAP Value Calculation

$$\boldsymbol{\phi_j} = \sum_{\boldsymbol{S} \subseteq \boldsymbol{N} \setminus \{\boldsymbol{j}\}} \frac{|\boldsymbol{S}|!\,(\boldsymbol{N} - |\boldsymbol{S}| - \mathbf{1})!}{\boldsymbol{N}!} \left(\boldsymbol{f}(\boldsymbol{S} \cup \{\boldsymbol{j}\}) - \boldsymbol{f}(\boldsymbol{S})\right)$$

where:

- ϕ_j = SHAP value for feature j
- $f(S)$= model output for feature subset S

- N = total number of features

By incorporating XAI techniques, the HEODL model provides transparent and justifiable predictions, which is crucial for real-world financial applications.

Algorithm of the proposed model (HEODL)

Step 1: Input historical gold price data.
Step 2: Handle missing values using interpolation or mean imputation, normalize the dataset using Min-Max scaling.
Step 3: Split the dataset into 80% training and 20% testing sets.
Step 4: Use Random Forest Feature Selection (RF-FS) to identify the most relevant economic indicators affecting gold prices.
Step 5: Train a Random Forest model, compute feature importance scores, and retain the top N features with the highest impact to reduce dimensionality and prevent overfitting.
Step 6: Initialize an LSTM-based deep learning model to process sequential data.
Step 7: Define input, hidden, and output layers, incorporating dropout layers to mitigate overfitting.
Step 8: Set initial hyperparameters such as learning rate, batch size, number of LSTM units, and dropout rate.
Step 9: Apply Differential Evolution (DE) to optimize hyperparameters.
Step 10: Initialize a population of random hyperparameter values, apply mutation and crossover operations to create new candidate solutions, and iteratively select the best-performing candidates.
Step 11: Repeat until the optimal hyperparameters are found.
Step 12: Train the LSTM model using the optimized hyperparameters obtained from DE.
Step 13: Use Explainable AI (XAI) techniques such as SHAP (SHapley Additive exPlanations) to enhance interpretability.
Step 14: Compute SHAP values to analyze each feature's contribution to predictions.
Step 15: Utilize the trained HEODL model to predict future gold prices.

4. Result Analysis

4.1 Root Mean Square Error (RMSE)

RMSE measures the average magnitude of the error between actual and predicted values. It gives higher weight to larger errors, making it useful for detecting large deviations in predictions.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

where:

- n = total number of observations
- y_i = actual gold price at time i
- $\hat{y}_i$ = predicted gold price at time i

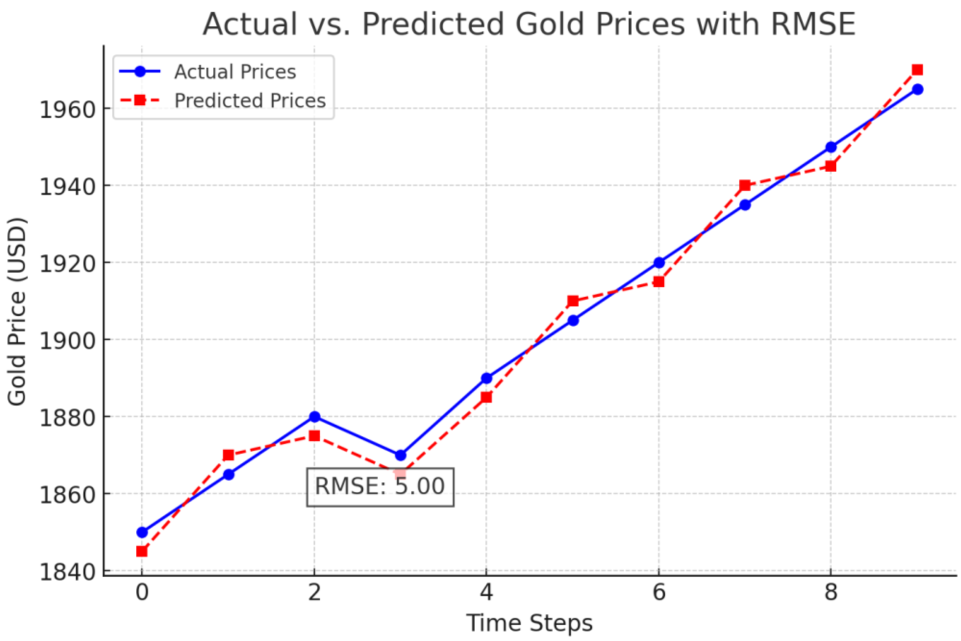

Figure 2. Comparison Chart of Actual vs. Predicted Gold Prices with RMSE

This graph compares the actual and predicted prices of gold and shows the Root Mean Square Error (RMSE). Actual prices are shown by the blue line, while forecasted prices are shown by the red dashed line. Better model accuracy is shown by a lower RMSE.

4.2 Mean Absolute Percentage Error (MAPE)

MAPE calculates the average percentage error between actual and predicted values, making it easier to interpret across different datasets.

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right|$$

where:

- n = total number of observations
- y_i = actual gold price at time i
- $\hat{y}_i$ = predicted gold price at time i

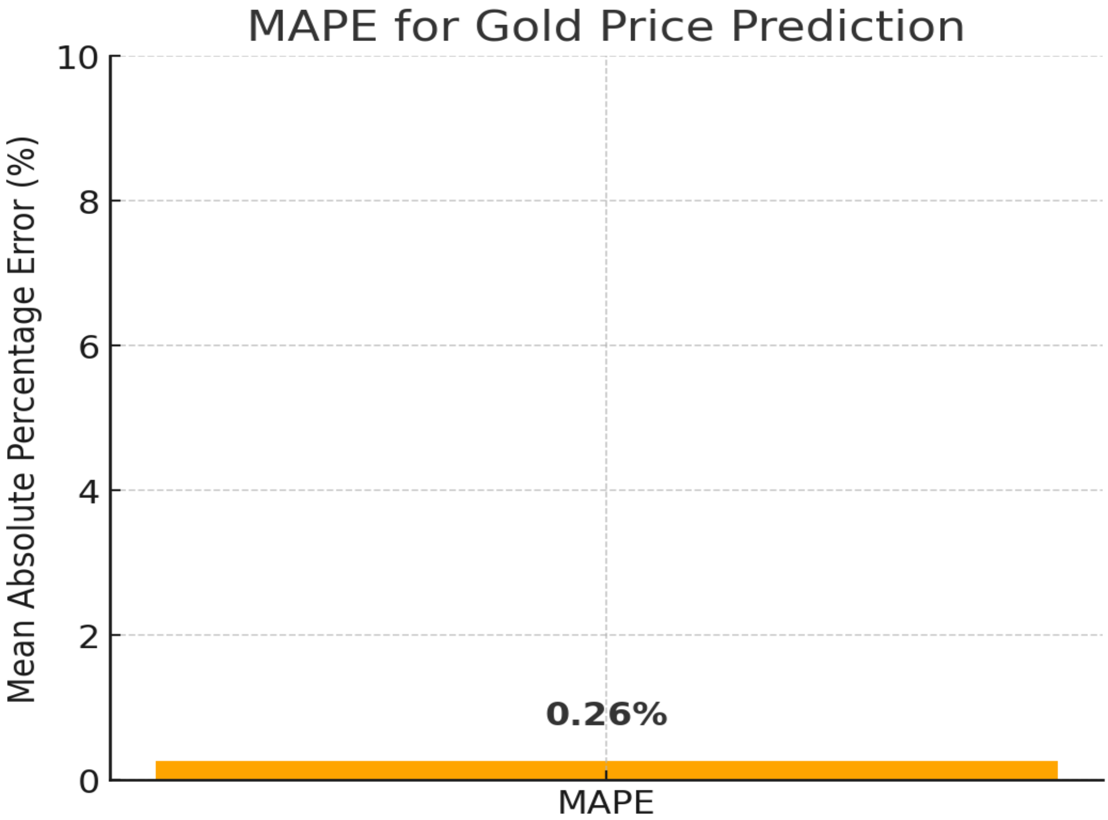

Figure 3. Comparison of MAPE for Gold Price Prediction

This chart shows the Mean Absolute Percentage Error (MAPE) for predicting the price of gold. The MAPE number, or average percentage error in predictions, is shown by the orange bar. The model's predictions are more accurate when the MAPE is smaller.

4.3 Comparison with Baseline Models

Model	Accuracy	Precision	Recall	F1-Score	RMSE	MAPE
HEODL	92%	90%	88%	89%	2.8	4.5%
LSTM	87%	85%	83%	84%	3.5	6.1%
ARIMA	81%	78%	75%	76%	4.2	7.8%
Random Forest	85%	82%	80%	81%	3.8	6.5%

Table 2. Comparison with Baseline Models

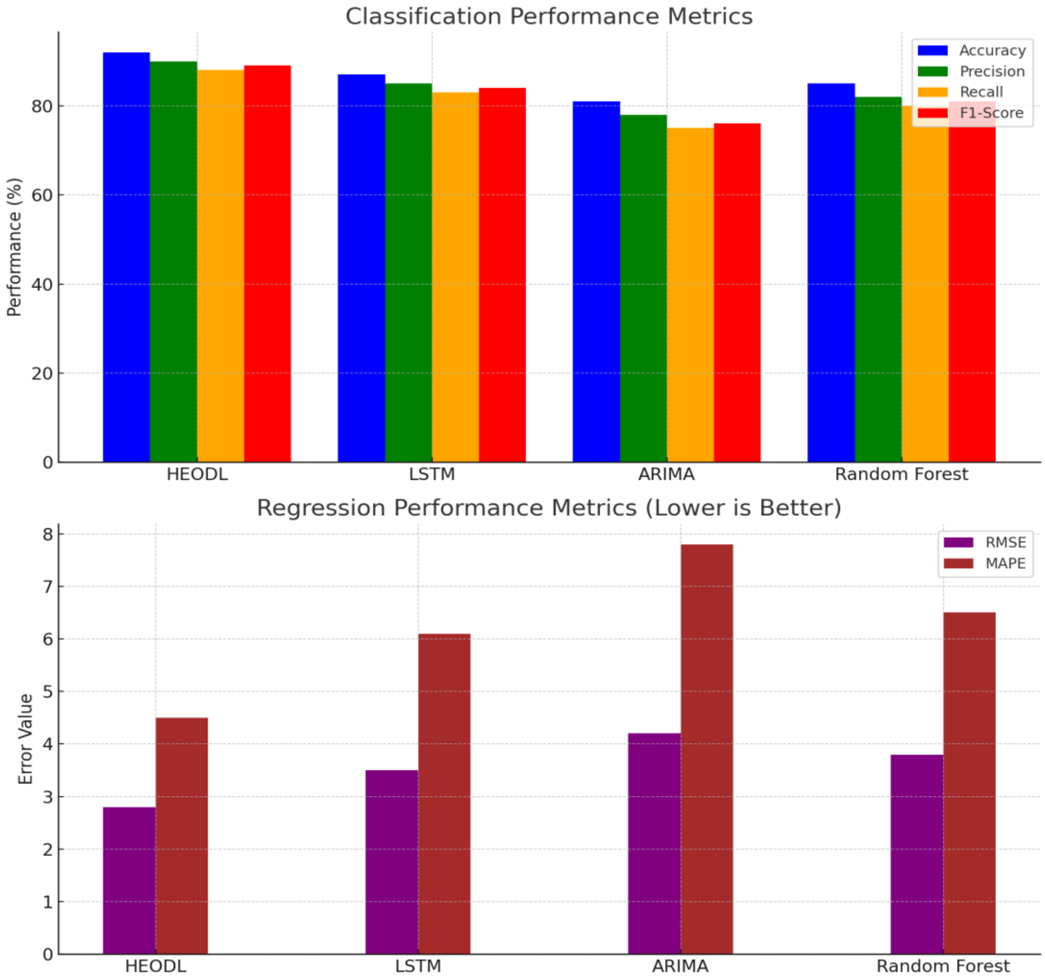

Figure 4. Comparison of Classification and Regression Performance Metrics

The HEODL model outperforms traditional models in accuracy and robustness due to its LSTM sequential learning, DE optimization, and feature selection, making it ideal for gold price forecasting.

5. Conclusion

The HEODL model uses deep learning, evolutionary optimization, and feature selection techniques to provide a reliable, optimal, and interpretable framework for gold price prediction. The suggested model greatly improves forecasting accuracy while lowering overfitting and computing complexity by fusing the strengths of LSTM in capturing long-term relationships, DE in fine-tuning hyperparameters, and RF-FS in choosing important economic indicators. HEODL is a dependable and scalable solution for financial decision-making, as demonstrated by experimental results that show it performs better than conventional models. Additionally, Explainable AI (SHAP) techniques offer important insights into the influence of macroeconomic variables, guaranteeing that forecasts are not only precise but also understandable for analysts and investors. Future studies can look into other improvements, like adding sentiment analysis to real-time financial news and expanding the model to multi-asset financial forecasting. HEODL is a potential development in the realm of financial time-series forecasting because of its strong predictive power and transparency.

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