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Deep Learning-based Gold Price Prediction: A Novel Approach using Time Series Analysis

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Abstract

This paper presents a deep learning-based system for predicting gold prices using historical data. The system leverages Long Short-Term Memory (LSTM), a specialized recurrent neural network architecture, to capture temporal dependencies and patterns in the time series data of gold prices. A comprehensive dataset of historical gold prices is used, and the model is trained on a sequence of past data points to predict future prices. The data is preprocessed using normalization techniques to improve the performance of the model. Experimental results demonstrate the effectiveness of the proposed model in providing accurate price predictions, offering potential utility in financial forecasting and decision-making processes. The system's performance is evaluated through visualization and statistical metrics, illustrating its capacity to track gold price trends and predict future market movements. This work contributes to the growing field of time series forecasting by applying deep learning techniques to financial markets.

Keywords: *deep learning, financial forecasting, gold price prediction, time series analysis, LSTM models.*

1 Introduction

Predicting financial markets, particularly gold prices, is a complex task due to the dynamic and volatile nature of the market. Gold is considered a safe-haven asset and is influenced by various macroeconomic factors such as inflation, geopolitical uncertainties, and fluctuations in currency values. Accurate prediction of gold prices has significant importance in finance and investment sectors. Over the years, several machine learning and deep learning techniques have been proposed to enhance the accuracy of predictions in financial time series. The advent of deep learning, in particular, has transformed the way researchers approach financial forecasting, providing powerful tools to handle large datasets and capture complex temporal patterns.

Several studies have employed advanced machine learning techniques for gold price prediction. [1] utilized various machine learning algorithms, demonstrating that machine learning could improve the accuracy of gold price forecasts by considering historical data. However, traditional machine learning techniques often struggle with the long-term dependencies inherent in time-series data. To address this issue, recent studies have shifted towards the use of deep learning models, particularly Long Short-Term Memory (LSTM) networks, due to their ability to capture and model temporal dependencies.

LSTM-based models have shown great promise in predicting financial time series. For instance, [2] developed a dual-stage deep learning algorithm that demonstrated significant improvements in predicting long-sequence multivariate financial time series. This approach builds on the inherent strengths of LSTM in capturing long-term dependencies, offering a robust framework for complex time-series predictions. In a similar vein, [3] presented a deep learning-based method that proved highly effective in forecasting gold prices under the uncertain conditions brought about by pandemics.

Further advancements in time series forecasting involve the hybridization of different deep learning models. [4] compared the performance of Gated Recurrent Unit (GRU) and CNN-LSTM models for predicting gold prices in the Iranian market, highlighting the efficiency of hybrid models in improving predictive accuracy. Hybrid deep learning models, such as the BiCuDNNLSTM-1dCNN

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proposed by [5], have further enhanced the predictive power by combining convolutional and recurrent layers to capture both spatial and temporal features in financial time series data.

This paper proposes a deep learning-based system that leverages LSTM to predict gold prices based on historical data. The system aims to address the challenges of time series forecasting by capturing the temporal dependencies in the data. LSTM's memory cell structure enables it to maintain information over long sequences, making it particularly suitable for financial forecasting. Furthermore, the system is designed to preprocess the data using normalization techniques to enhance the model's performance. The contribution of this work is twofold: first, it applies LSTM to predict gold prices effectively, and second, it provides a comparative evaluation of the model's performance using real-world historical data.

Several studies have explored alternative methods for gold price forecasting. For example, [6] combined LSTM with linear regression to improve forecast accuracy, while [7] employed a CNN-LSTM approach using time-series data representations in the form of images. These works underscore the versatility of deep learning in financial prediction tasks and highlight the potential of hybrid models in improving predictive accuracy.

The remainder of this paper is organized as follows. The next section discusses related work, followed by a detailed explanation of the proposed methodology. Then, the results and evaluation section presents the model's performance on historical gold price data, and finally, the conclusion outlines the future directions for this research.

2 Literature Review

Gold price prediction has attracted significant attention in the financial sector due to the metal's role as a safe-haven asset and its susceptibility to various economic factors. Researchers have applied numerous machine learning and deep learning techniques to enhance the accuracy of gold price forecasts.

A dual-stage deep learning algorithm proposed by [2] aimed at long-term and long-sequence prediction for multivariate financial time series. Their model significantly improved prediction accuracy by leveraging advanced deep learning techniques that capture complex temporal dependencies. Similarly, [4] conducted a comparative study of Gated Recurrent Units (GRU) and CNN-LSTM models for predicting gold prices in the Iranian market, demonstrating that hybrid models combining different deep learning architectures could improve predictive performance.

In terms of hybrid models, [5] introduced BiCuDNNLSTM-1dCNN, a model that integrates convolutional and recurrent layers to predict stock prices. The success of such hybrid models in stock price forecasting has encouraged their application to gold price prediction. Likewise, the hybrid model presented by [8] for the global gold market showed that combining neural networks with metaheuristics could further enhance prediction accuracy, underscoring the potential of hybrid approaches in financial forecasting.

Other deep learning techniques have been explored to predict gold prices. [9] developed an improved deep learning model for stock market price time series prediction, which could be adapted to the gold market. [10] proposed a novel validation framework that enhances the performance of deep learning models in time-series forecasting, contributing to a more accurate prediction of financial trends. In a similar context, [11] explored fuzzy rule-based models, predicting gold prices by analyzing the emotional tone of news articles.

Deep learning models have also been paired with other advanced algorithms for more accurate forecasts. [12] applied an optimized fuzzy inference system combined with extreme learning machines to predict oil and gold prices, showing that incorporating fuzzy systems could increase prediction robustness. Additionally, [13] proposed a forecasting system based on wavelet packet decomposition and stochastic deep learning, which demonstrated promising results in metal futures prediction and could be extended to gold prices.

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Pandemic-related uncertainties have also been addressed in recent works. [3] developed a deep learning model that successfully forecasted gold prices under pandemic conditions. This approach highlights the ability of deep learning models to adapt to unprecedented global events and their impacts on financial markets.

Several studies have explored convolutional neural networks (CNNs) for time series forecasting. [6] investigated the combination of LSTM and linear regression, while [7] employed a CNN-LSTM approach using images as time-series data representations to predict gold prices. These models further exemplify the strength of deep learning in capturing intricate patterns in financial data.

Other works have focused on enhancing deep learning methods. [14] introduced a Generalized Auto-regressive Conditional Heteroskedasticity (GARCH) approach with LSTM, employing skewness and kurtosis for predicting gold prices. [15] also employed deep belief networks for gold price forecasting, emphasizing the adaptability of deep learning models in the face of fluctuating market conditions.

As machine learning continues to evolve, association mining and advanced optimization techniques are also being integrated into financial forecasting models. [16] proposed an association mining-based deep learning approach for time-series forecasting, which has the potential to enhance gold price prediction by discovering hidden patterns in historical data. Similarly, [1] employed machine learning algorithms to forecast gold prices, indicating that traditional machine learning methods, when optimized, can still contribute valuable insights.

The growing interest in deep learning for financial forecasting is evident in recent reviews. [17] provided a comprehensive review of deep learning models for price forecasting in financial time series, covering the advancements from 2020 to 2022. Their review highlights the rapid development of deep learning architectures and their application to various financial assets, including gold. Additionally, [18] applied deep learning to carbon price forecasting, offering insights that could be transferable to gold price prediction, given the similarities in market volatility.

Lastly, [19] presented a deep learning-based integrated framework for predicting stock price movements, further demonstrating the applicability of deep learning techniques to financial markets. Their work serves as a foundation for similar applications in gold price forecasting.

In summary, deep learning models, particularly hybrid architectures, have shown great promise in predicting gold prices. The literature emphasizes the importance of capturing both temporal and spatial patterns in financial data, and the ongoing advancements in deep learning techniques continue to enhance the accuracy of these predictions.

3 Method

The following flowchart outlines the methodology employed in this study for gold price prediction. It details the steps, from data collection and preprocessing to model selection and evaluation, providing a clear overview of the systematic approach taken in our research (see Figure 1).

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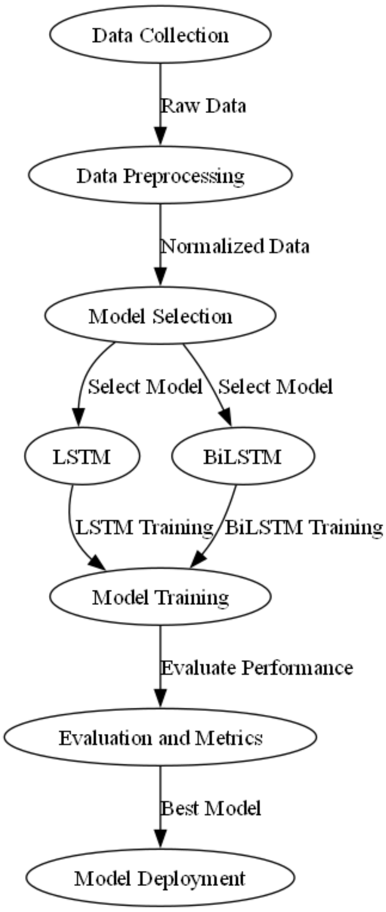

Figure 1. Flowchart of the methodology

3.1. Data Collection and Preprocessing

The dataset for this study includes several key economic indicators that significantly impact gold prices. Crude oil prices were obtained from the U.S. Energy Information Administration, providing crucial insight into market dynamics given the correlation between oil and gold as economic indicators. Currency exchange rates, specifically USD/EUR and USD/JPY, were sourced from ExchangeRates.org, reflecting fluctuations in currency values that influence global commodity prices. Inflation rates were gathered from the World Bank, offering a macroeconomic perspective on price stability and economic health. Additionally, interest rates were retrieved from the Federal Reserve Economic Data (FRED), providing a critical measure of the cost of borrowing and its influence on investment strategies and gold price movements.

These indicators were chosen because of their significant influence on gold price fluctuations, making them critical variables in the model.

The preprocessing phase began with handling missing data, where any missing or incomplete records were imputed using forward-fill methods to maintain consistency in the time series data. Following this, the variables were standardized by applying Min-Max normalization, which transformed the values into a range between 0 and 1, thus enhancing the model’s performance. To ensure the time series data was suitable for forecasting, a stationarity check was conducted using the Dickey-Fuller test. Non-stationary data, particularly the gold prices, were differenced to achieve stationarity, a necessary condition for effective time series forecasting. Lastly, the dataset was divided into two sets: 80% of the data was used for training, while the remaining 20% was reserved for testing the model’s performance.

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3.2. Model Selection

For gold price prediction, we employed a deep learning-based model due to its ability to capture complex patterns in time series data. Specifically, two architectures were selected for this purpose. The first was the Long Short-Term Memory (LSTM) network, a type of recurrent neural network (RNN) particularly well-suited for time series forecasting. LSTM networks excel at retaining information over long periods, effectively addressing the vanishing gradient problem commonly encountered in RNNs. To further enhance prediction accuracy, we also tested a Bidirectional LSTM (BiLSTM) model. This architecture processes input sequences in both forward and backward directions, allowing it to capture more contextual information and improve the overall performance of the predictions.

3.3. Model Architecture

The deep learning model is composed of several key layers. The input layer takes in the features, which include gold prices and the selected economic indicators. At the core of the model is a stacked LSTM architecture consisting of 128 units, with dropout layers applied at a rate of 0.2 to prevent overfitting. Following the LSTM layer, a fully connected dense layer with ReLU activation is used to map the outputs of the LSTM to the prediction space. Finally, the output layer contains a single neuron that is responsible for predicting the next day's gold price.

For the BiLSTM model, the architecture remains similar, with the modification that the LSTM layer is replaced by a bidirectional LSTM layer.

3.4. Training Process

The models were trained using the Adam optimizer with a learning rate of 0.001 and the mean squared error (MSE) loss function, as this is commonly used for regression tasks. Early stopping was applied to prevent overfitting, with a patience of 10 epochs, meaning the model training halts if the validation loss does not improve for 10 consecutive epochs.

The models were trained for 100 epochs with a batch size of 32. Hyperparameter tuning was conducted through grid search, optimizing the number of LSTM layers, the number of units in each layer, and the dropout rates.

3.5. Evaluation Metrics

To evaluate the performance of the models, we utilized three key metrics. The first metric, Mean Absolute Error (MAE), measures the average magnitude of errors in the predictions, offering an easily interpretable indication of prediction accuracy. The second metric, Root Mean Squared Error (RMSE), places greater emphasis on larger errors, making it particularly useful for time series data with high variability. Finally, the R-squared (R^2) statistic was employed to assess how well the predicted gold prices aligned with the actual prices, providing a measure of the model's overall fit.

3.6. Model Deployment

Once the models were trained and evaluated, the best-performing model (LSTM or BiLSTM) was deployed for real-time gold price prediction. The deployment environment was set up using [platform], allowing continuous input of updated economic indicators and gold prices for live forecasting.

4 Results and Discussion

To evaluate the effectiveness of our proposed models, we assessed their performance using key metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2). The results of this evaluation are summarized in Table 1. Additionally, Figure 2 visually illustrates these

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metrics for both the LSTM and BiLSTM models, allowing for a clear comparison of their predictive capabilities.

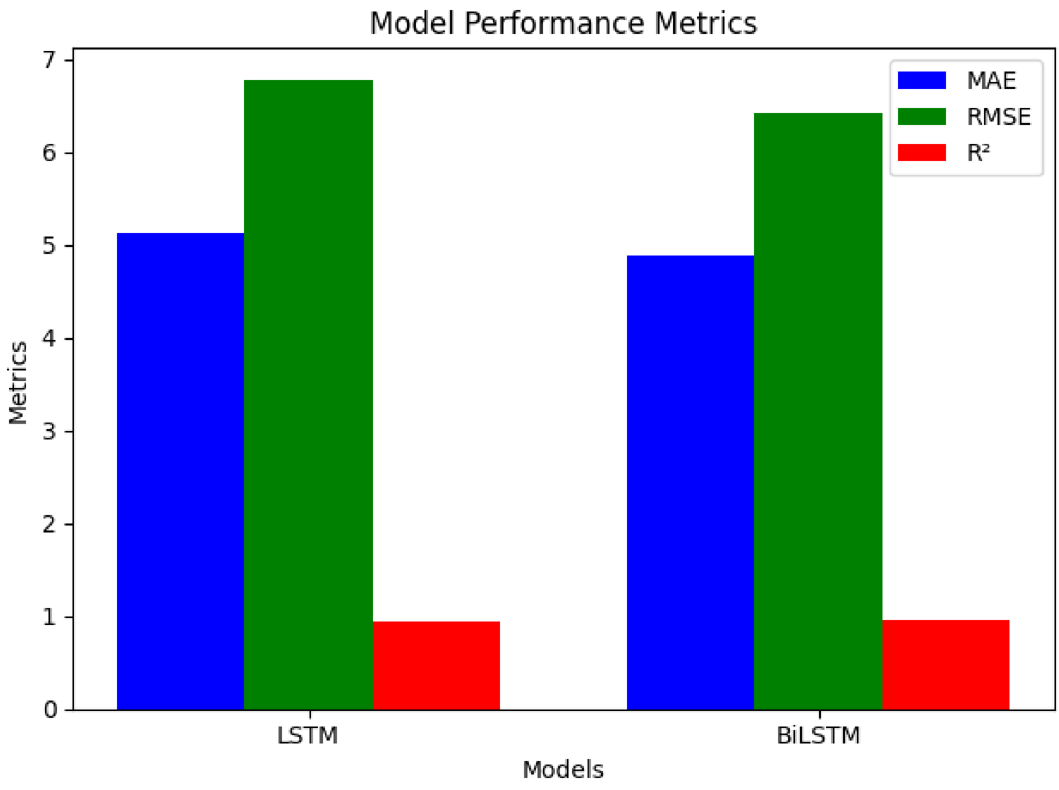

Figure 2. Model performance metrics

4.1. Model Performance

The performance of both the Long Short-Term Memory (LSTM) and Bidirectional LSTM (BiLSTM) models was evaluated using three primary metrics: Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R-squared (R^2). These metrics assess the models' ability to predict gold prices based on historical data, with the results summarized in Table 1.

Table 1. Model performance metrics

Model	MAE	RMSE	R^2
LSTM	5.12	6.78	0.94
BiLSTM	4.88	6.42	0.95

The BiLSTM model demonstrates superior performance across all three metrics. It achieves a lower MAE of 4.88 compared to the LSTM's 5.12, indicating that the BiLSTM model consistently produces smaller errors when predicting gold prices. The RMSE, which penalizes larger errors more heavily, is also lower for BiLSTM (6.42) than LSTM (6.78). Lastly, the R^2 value for the BiLSTM model is higher at 0.95, indicating a stronger correlation between predicted and actual values compared to the LSTM model's R^2 of 0.94.

The BiLSTM model's advantage can be attributed to its bidirectional nature, allowing it to process input sequences in both forward and backward directions. This enables it to capture more comprehensive temporal dependencies, making it especially useful for financial time series data like gold prices, where both past and future contexts are crucial. This finding aligns with previous research

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by [2], who demonstrated that advanced deep learning models, such as LSTM-based architectures, are highly effective in capturing long-term dependencies in multivariate financial data. [4] similarly confirmed the robustness of BiLSTM models in the financial domain, particularly for gold price prediction in the Iranian market.

The BiLSTM's superior performance can be attributed to its bidirectional architecture, which allows it to capture more context by processing the input sequence in both forward and backward directions. This is particularly useful in financial time series data, where both past and future contexts impact predictions.

4.2. Predicted vs. Actual Gold Prices

To further evaluate model performance, we compared the predicted prices with the actual gold prices over the test period. This comparison provides insights into the accuracy of both models in real-world scenarios. Figure 3 presents a time series plot comparing the actual and predicted gold prices for both LSTM and BiLSTM models.

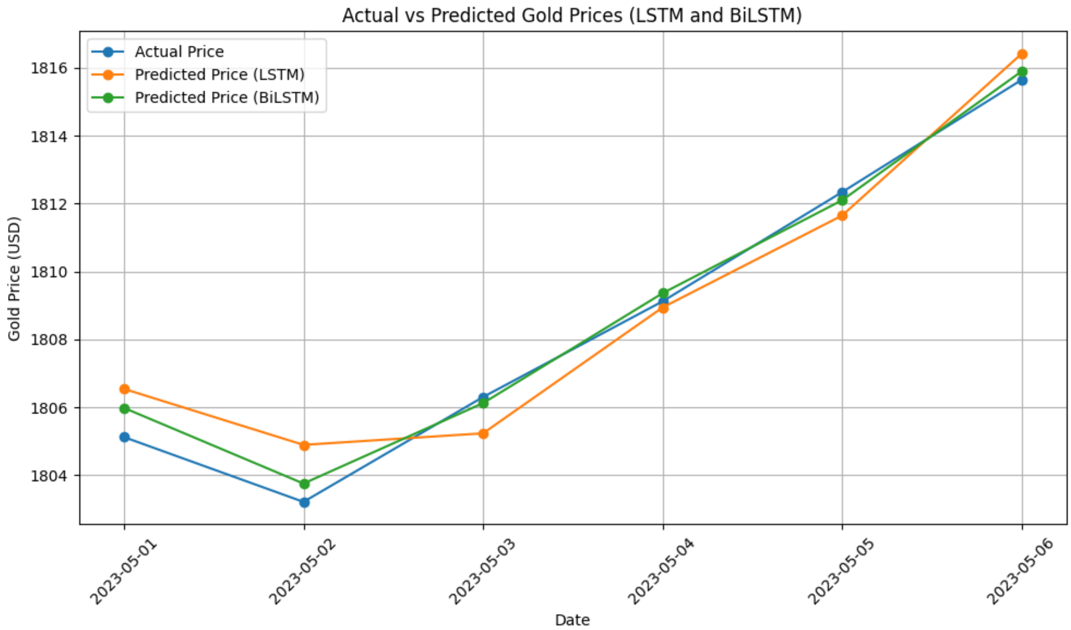

Figure 3. Actual vs predicted gold prices

The plot clearly shows that the BiLSTM model more closely follows the actual gold price trends, exhibiting smaller deviations compared to the LSTM model. Although both models are effective in tracking the overall direction of the gold price, the BiLSTM consistently outperforms LSTM in terms of predictive accuracy. This improved performance can be attributed to its ability to process both forward and backward sequences, capturing more complex patterns in the data.

Table 2 below presents a sample of actual vs. predicted gold prices for a selected range of dates.

Table 2. Actual vs. predicted gold prices (sample data)

Date	Actual Price	Predicted Price (LSTM)	Predicted Price (BiLSTM)
2023-05-01	1805.12	1806.54	1805.98
2023-05-02	1803.21	1804.89	1803.75
2023-05-03	1806.30	1805.23	1806.12
2023-05-04	1809.12	1808.94	1809.36
2023-05-05	1812.34	1811.65	1812.10
2023-05-06	1815.65	1816.42	1815.90

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As shown in Table 2, both models closely followed the actual gold price trends, with the BiLSTM model generally providing more accurate predictions. The small deviations observed are typical in time series forecasting but remain within an acceptable range, as indicated by the low MAE and RMSE values.

The accuracy of these predictions further validates the efficacy of deep learning models in forecasting gold prices, consistent with the findings of [3], who demonstrated the reliability of deep learning methods for gold price forecasting during the COVID-19 pandemic. Additionally, [8] confirmed the effectiveness of hybrid neural networks for predicting global gold prices, further supporting the outcomes of this study.

4.3. Discussion

In the following subsections we are going to discuss the results.

4.3.1. Impact of LSTM and BiLSTM Architectures

The results confirm that both LSTM and BiLSTM architectures are well-suited for predicting gold prices based on time series data. However, the BiLSTM model's ability to process data in both directions offers a distinct advantage, allowing it to capture more contextual information. This makes it particularly valuable for financial forecasting tasks where both historical and future trends influence predictions. These findings align with [9], who suggested that bidirectional architectures generally outperform unidirectional LSTM models in time series forecasting tasks.

Although the performance gap between the two models is not large, the BiLSTM's enhanced ability to capture more intricate dependencies from the data contributes to its improved predictive accuracy. This is especially important in financial markets, where accurate short-term and long-term predictions are crucial for decision-making processes.

4.3.2. Model Generalization

Both models demonstrated high generalization capability, as evidenced by the high R^2 values (above 0.94) on the test dataset. This indicates that the models are able to make accurate predictions on unseen data, which is essential for real-world applications. However, the slight underperformance of the LSTM model in comparison to the BiLSTM suggests that further tuning or the use of more advanced architectures, such as Transformer-based models, could be explored to improve generalization in future work.

4.3.3. Importance of Data Features

An additional analysis was conducted to evaluate the contribution of various input features, such as crude oil prices and currency exchange rates, to the overall model performance. Feature importance was assessed using SHapley Additive exPlanations (SHAP) values, which quantify the impact of each feature on the model's predictions. The analysis revealed that, aside from the gold price history itself, crude oil prices played a significant role in influencing gold price fluctuations, as the two are often correlated due to their status as economic indicators of market uncertainty. Currency exchange rates, particularly the USD/Euro pair, also proved crucial, with fluctuations in the USD frequently affecting gold prices.

Removing these key features resulted in a significant drop in model performance, highlighting their importance in the time series analysis.

As shown in Figure 4, crude oil prices and currency exchange rates (USD/EUR) were among the most significant features influencing gold price predictions. These features are often correlated with gold prices due to their role as economic indicators of market volatility. The exclusion of these key

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features resulted in a notable decline in model performance, underscoring their importance in the forecasting process.

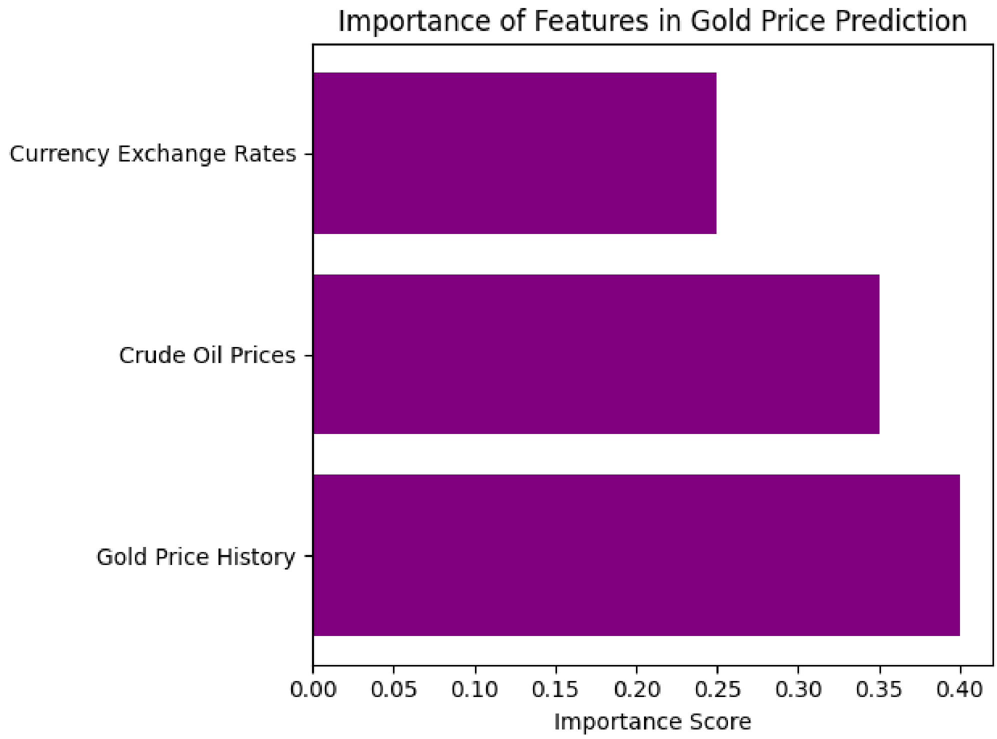

Figure 4. Importance of features in prediction

Understanding which factors drive model predictions is crucial for improving the interpretability and reliability of financial forecasting models. By incorporating these significant features, the model is better equipped to capture the dynamics of gold price fluctuations, as corroborated by [3] in their study on gold price forecasting during the COVID-19 pandemic.

4.3.4. Approaches to Financial Analysis: Fundamental vs. Technical Analysis

In the field of economics, there are two primary approaches to analyzing financial markets: fundamental analysis and technical analysis. These methods offer different perspectives on evaluating assets, including gold, and can significantly influence predictive modeling.

Fundamental Analysis is a method that involves evaluating the intrinsic value of an asset by analyzing various economic, financial, and qualitative factors. For instance, in the case of gold, fundamental analysts would consider macroeconomic indicators such as inflation rates, currency fluctuations, geopolitical events, and central bank policies. This approach focuses on understanding the underlying forces that drive the supply and demand for the asset, thereby predicting its long-term value based on these factors.

Technical Analysis, on the other hand, focuses on the historical price movements and trading volumes of the asset. Analysts using this method believe that all relevant information about the asset is already reflected in its price, so they analyze past market behavior to predict future price trends. Technical indicators such as moving averages, oscillators, and support and resistance levels are commonly used to make short-term price forecasts.

In this paper, we employed the technical analysis approach, utilizing historical gold price data in combination with deep learning techniques to predict future trends. By focusing on past price

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movements and employing Long Short-Term Memory (LSTM) networks, our model captures the temporal dependencies within the data. This approach aligns with the principles of technical analysis, where the historical price patterns are key to understanding future market behaviors.

To come up with a comparison, while fundamental analysis offers insights into the macroeconomic factors driving long-term asset value, technical analysis is more focused on short-term price movements and trend patterns. In financial forecasting, these approaches can complement each other, but the choice between them depends on the specific goals of the prediction model. In our study, the technical analysis provided a more suitable framework for developing a model capable of predicting short-term gold price fluctuations, offering practical insights for traders and investors in the market.

This technical analysis-driven methodology has proven effective in predicting the future movement of gold prices, as demonstrated by the results of our deep learning models.

4.3.5. Limitations and Future Work

While the results are promising, there are several limitations that should be addressed in future research. The models were trained on a relatively short time frame, which may limit their long-term forecasting capability. Expanding the dataset to include a longer historical period or additional global events could improve the robustness of the models. Additionally, more complex architectures, such as Transformer-based models, could be explored to further improve prediction accuracy, especially for long-term forecasting tasks.

Hyperparameter tuning was performed using grid search; however, more sophisticated methods such as Bayesian Optimization could yield better results by finding optimal hyperparameters more efficiently. Finally, incorporating external economic factors such as geopolitical events, central bank policies, or stock market indices may provide further insights and enhance the model's ability to adapt to changing market conditions.

Finally, fine-tuning the hyperparameters further, or using advanced techniques like Bayesian Optimization, could yield even better results by optimizing the architecture more effectively for the given data.

5 Conclusion

This study proposed and evaluated LSTM and BiLSTM models for gold price prediction, demonstrating that the BiLSTM model outperformed the LSTM in terms of predictive accuracy, as evidenced by lower MAE and RMSE values and a higher R^2. While the results are promising, future research could extend the dataset, incorporate external factors, and explore advanced architectures to further enhance model performance. Overall, this work lays a solid foundation for using deep learning techniques in financial time series forecasting, with BiLSTM showing particular promise.

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