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Predicting Gold Price Movement Using Long Short-Term Memory Model

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Abstract – Gold, as a valuable commodity, has been a primary focus in the global financial market. It is often utilized as an investment instrument due to the belief in its potential price appreciation. However, the unpredictable and complex movement of gold prices poses a significant challenge in investment decision-making. Therefore, this research aims to address this issue by proposing the use of the Long Short-Term Memory (LSTM) model in time series analysis. LSTM is a robust approach to understanding patterns and trends in gold price data over time. In the context of time series analysis, historical gold price data includes daily, weekly, and monthly datasets. Each model with its respective dataset is useful for identifying patterns in gold prices. The daily model achieves an MSE of 452.2284140627481 and an RMSE of 21.26566279387379. The weekly model achieves an MSE of 1346.1816584357384 and an RMSE of 36.69034830082345. The monthly model achieves an MSE of 11649.597907584808 and an RMSE of 107.93330305139747. With these RMSE results, the LSTM model can predict gold prices effectively. Based on the trained models, it can also be concluded that gold prices exhibit long-term temporal dependence.

Keywords - Long Short-Term Memory, Gold Price Prediction, Time series analysis

1. INTRODUCTION

Gold is a traded commodity and also serves as a financial asset. Gold tends to resemble more of a financial asset than commodities like stocks or bonds, which have long-term investment horizons [1]. Gold is also considered a last resort for investors when the global capital markets fail to deliver desired returns. Therefore, it can be said that investors view gold as a tool to hedge against fluctuations in other markets.

The increase in the value of gold alongside fluctuations in prices in other markets such as the stock market and real estate has attracted more investors towards gold as an attractive investment. However, recently the price of gold has also experienced high volatility, making investments in gold riskier[1]. Hence, given its importance, accurately predicting the price of gold can be efficiently used to navigate the market according to anticipated future trends. Accurate gold price forecasting models can be utilized by clients to prevent or mitigate potential risks, thereby reducing financial losses and potential bankruptcy.

However, various types of uncertainties have the potential to have different impacts on the price of gold. During the COVID-19 pandemic, gold investments experienced a significant increase as prospective investors shifted from stocks affected by the decline in stock market indices in several countries [2].

Traditional forecasting methods for predicting the price of gold involve Autoregressive Integrated Moving Average (ARIMA) [3], 2020) and multi-linear regression [4]. With the advancement of artificial intelligence, many computing methods have also been used for gold price forecasting. Artificial Neural Networks (ANN) have emerged as a primary technique for constructing predictive models, alongside other soft computing methods like Recurrent Neural Network (RNN) specifically tailored for time series analysis [5].

In the short term, the market tends to behave like a voting machine, but in the long term, the market behaves like a weighing machine, thus there is potential to forecast market movements over longer time frames [6]. Technical analysis can be used to predict future gold prices. One of the technical analyses that can be used to predict gold prices is time series analysis, where price movements are associated with events that occurred in the past [7] such as daily, weekly, and monthly prices in the past. Therefore, in this study, the Long Short-Term Memory (LSTM) model is used to predict gold prices based on time series analysis.

The LSTM model is a variant of the RNN model that has the ability to process previously stored information in long and diverse sequences. LSTM is specifically designed to understand and predict sequential data over long time spans. In this study, the LSTM model is used to make predictions based on daily, weekly, and monthly time series. Each time series will be given different timesteps based on the time range, the longer the time range, the shorter the timesteps will be given while still estimating how much past prices can influence current conditions to predict future prices. In the model creation process, a grid search process will be conducted to find the best timesteps for each time series.

Therefore, the use of LSTM for predicting historical gold prices is a suitable choice due to its appropriate capabilities. The use of LSTM for gold price prediction can help investors understand the fluctuations and patterns behind historical trends and estimate behaviors in future steps, thereby adding an analytical component to investment decision-making and economic analysis.

2. RESEARCH METHOD

2.1. Data Collection and Preprocessing

This study utilizes historical gold price data sourced from investing.com, covering daily data from December 29, 1978, to September 15, 2023; weekly data from January 5, 1975, to October 15, 2023; and monthly data from February 1, 1975, to October 1, 2023. The data, presented in US dollars per ounce, is processed for time series analysis using the Long Short-Term Memory (LSTM) model.

The gold price dataset undergoes thorough scrutiny to eliminate missing values, duplicates, or anomalies that may affect the analysis. Irrelevant attributes are removed, leaving only price and date as inputs for this study.

The gold price data undergoes formatting for time series analysis, including date and numerical adjustments, followed by chronological sorting. Subsequently, Min-Max Scaling is applied to standardize the data within a fixed range, typically between 0 and 1, reducing the impact of outliers. This scaling method simplifies machine learning computations. Finally, the scaled data is dimensionally adjusted to fit the LSTM model: [number of data points, timesteps, attributes].

The data is divided into two sets: the training set and the testing set. The training set is further partitioned into training and validation sets, with an 80-20 ratio, aiming to prevent overfitting to the testing data. The training set is utilized for LSTM model training, while the validation set assesses model performance and updates its parameters. Subsequently, the testing set gauges the model's effectiveness with previously unseen data, ensuring a robust evaluation of its performance.

2.2. Long-Short Term Memorry

Long Short-Term Memory (LSTM) was first introduced by Hochreiter and Schmidhuber in 1997 [8]. LSTM represents an advancement in the realm of Recurrent Neural Networks (RNN) within the domain of deep learning. Comprising three fundamental components, LSTM is engineered to effectively mitigate common challenges inherent in traditional RNN architectures [9].

In this study, the LSTM model is trained on various time series frequencies: daily, weekly, and monthly. Each frequency is assigned specific timesteps optimized to influence gold price predictions effectively. The model is developed using the Google Colab platform and TensorFlow framework, comprising 1 input layer, 2 hidden layers, and 1 output layer.

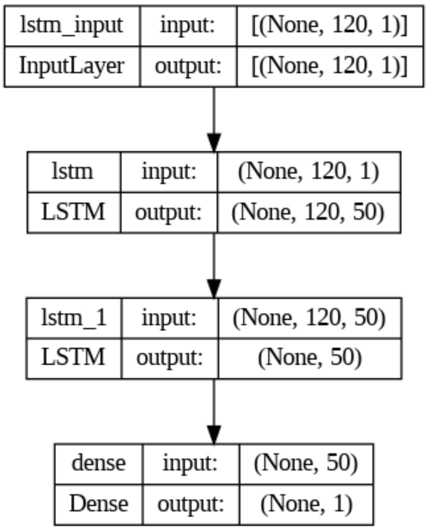

Figure 1. Illustrates an example of the LSTM model architecture

For instance, the model architecture, as depicted in Figure 3.1, illustrates the input layer with 1 variable and 120 timesteps, followed by a hidden layer of 50 units with 120 timesteps. The output layer generates 1 output for prediction results. This architecture enables the model to analyze patterns in gold price movements across different time series frequencies.

2.3. Mean Squared Error

Mean Squared Error (MSE) is a common metric used to evaluate the performance of a regression model. It calculates the average of the squares of the errors or the differences between actual and predicted values. The formula for Mean Squared Error is:

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

Where:
- n is the number of data points,
- y_i is the actual value,
- $\hat{y}_i$ s the predicted value.

A lower MSE indicates a better fit of the model to the data. It penalizes large errors more than small ones due to squaring the differences. MSE is widely used in various fields such as machine learning, statistics, and signal processing to assess model accuracy.

2.4. Root Mean Squared Error

The Root Mean Squared Error (RMSE) is a measure of the difference between predicted and actual values in a regression analysis. It is calculated by taking the square root of the average of the squared differences between the predicted and actual values. The RMSE is used to evaluate the accuracy of a predictive model, with lower values indicating better performance. The formula for Mean Squared Error is:

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

In terms of interpretation, the RMSE represents the standard deviation of the residuals, or the differences between the predicted and actual values. Therefore, a smaller RMSE indicates that the model is better at predicting the outcome variable.

3. RESULTS AND DISCUSSION

Here are examples of historical gold price data based on 10 random samples taken from daily dataset.

Table 1. The form of historical raw data for daily gold prices

Date	Price	Open	High	Low	Vol.	Change %
07/28/1986	356.9	354.9	356.0	354.8	0.01K	1.97%
11/14/1979	392.4	394.0	395.0	391.5	NaN	1.40%
01/20/1989	411.8	411.8	411.8	411.8	0.00K	1.20%
10/21/1980	668.0	663.0	671.0	657.0	27.05K	0.15%
12/20/1978	217.6	220.4	220.5	217.6	NaN	-2.73%
10/26/1993	370.3	369.5	370.5	367.6	24.05K	-0.05%
11/02/1981	437.6	437.6	437.6	437.6	NaN	0.30%
12/23/1981	408.0	405.5	408.5	403.2	26.64K	-0.10%
06/29/1992	346.0	346.0	346.0	346.0	NaN	0.61%
04/01/1975	179.1	179.7	179.7	178.4	NaN	-0.22%

The raw historical gold price data is initially examined for anomalies, missing data, and outliers to ensure data quality. During this data cleaning process, irrelevant attributes ('Open', 'High', 'Low', 'Vol. ', 'Change %') are removed, leaving only 'Date' and 'Price' attributes for analysis. Subsequently, the data is transformed by adjusting the 'Date' attribute to datetime64 format to clarify its time series nature. The 'Date' column is then set as the index for the dataframe, and redundant 'Date' column is dropped. The 'Price' attribute data type is changed to float64. The dataset is then sorted chronologically.

Next, data scaling is performed to normalize the 'Price' attribute values. Scaling data involves transforming the range of values within the dataset to a consistent scale, typically between 0 and 1, using Min-Max Scaling method. This ensures uniformity across variables, optimizes machine learning algorithm performance, and reduces the impact of outliers.

After scaling, the data is divided into training and testing sets with a ratio of 90%:10% to evaluate model performance and prevent overfitting. The formatted data is then reshaped into three-dimensional arrays to fit the LSTM model format, using the numpy library. The final three-dimensional array format is (number of data points, timesteps, 1), where the number of data points varies for each dataset, timesteps is a hyperparameter, and 1 denotes the single input attribute used for prediction. This format aligns with the LSTM model requirements.

Next, the model is trained on the preprocessed datasets using existing parameters to identify the optimal configuration. This phase involves implementing a grid search hyperparameter tuning loop to explore combinations of timesteps, units, and epochs that yield the best model performance. Through iterative evaluation of various hyperparameter combinations, the model identifies the optimal configuration that maximizes performance metrics.

Table 2. The parameters used for training

Parameters	**Values**
units	32, 50
epoch	50, 100
timesteps (daily)	60, 120, 180, 360
timesteps (weekly)	4, 8, 12, 20, 60, 180
timesteps (monthly)	3, 6, 12, 24, 36, 100

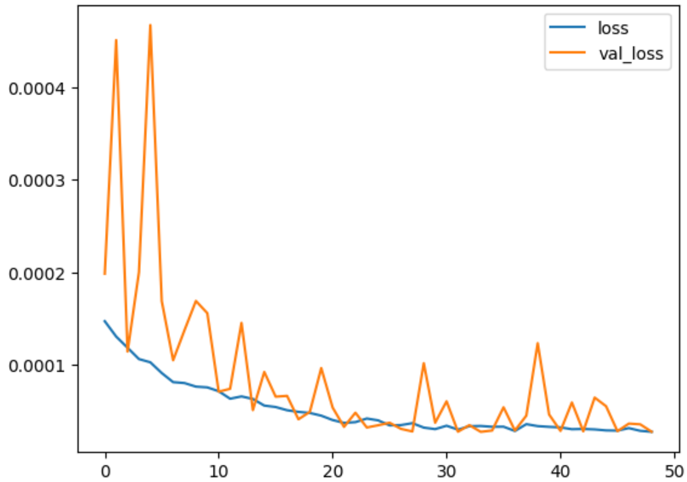

Figure 2. The loss graph based on the best results from training on the daily dataset

Following model training on each dataset, the lowest recorded `val_loss` for the daily dataset is 0.000027164696803083643. These parameters include timesteps = 120, units = 32, and epochs = 50. These results demonstrate that employing 32 units in each hidden layer and 50 epochs for training is sufficient to capture underlying patterns in the daily dataset. Utilizing 120 timesteps allows the model to effectively predict the next day's gold price, indicating the significance of the preceding 120 days' price data in forecasting future trends.

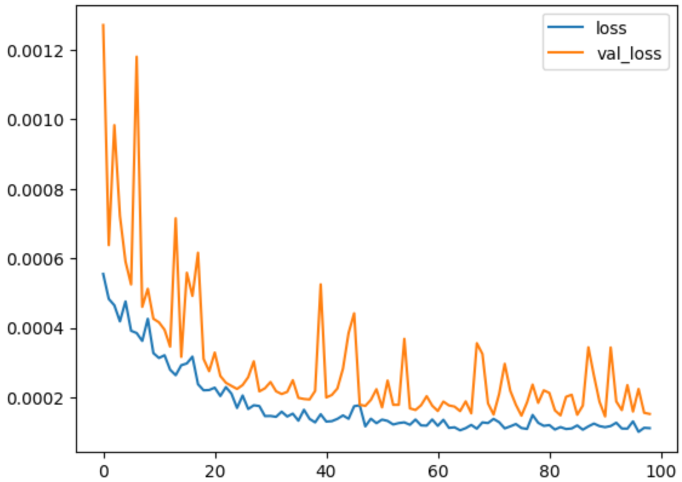

Figure 3. The loss graph based on the best results from training on the weekly dataset

For the weekly timeframe, the lowest recorded `val_loss` is 0.00015265439287759364, achieved with parameters: timesteps = 60, units = 50, and epochs = 100. These findings indicate that utilizing 50 units in each hidden layer and 100 epochs for training is sufficient to capture patterns in the weakly dataset. Utilizing 60 timesteps allows the model to effectively predict the next week's gold price, suggesting the significance of the preceding 60 weeks' price data in forecasting future trends.

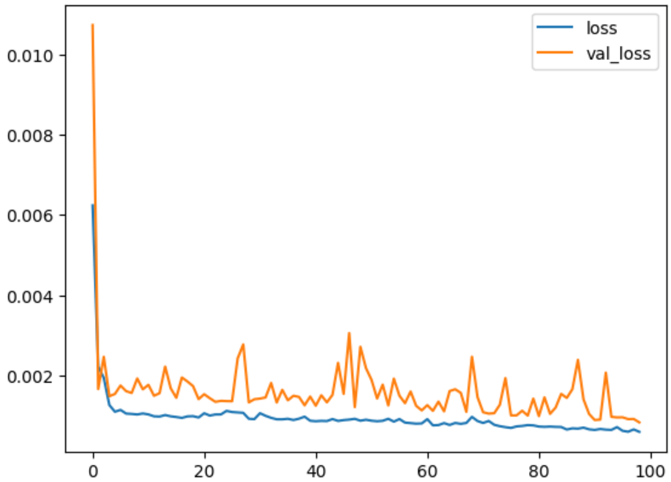

Figure 4. The loss graph based on the best results from training on the monthly dataset

In the case of the model trained on monthly datasets, the lowest recorded `val_loss` is 0.0008440767996944487, achieved with the following parameters: timesteps = 6, units = 50, and epochs = 100. These findings highlight that employing 50 units in each hidden layer and conducting training for 100 epochs results in the optimal model with the lowest validation loss. Utilizing 6 timesteps enables the model to effectively forecast the next month's gold price, underscoring the importance of the preceding 6 months' price data in predicting future trends.

Below is the table displaying the parameters and corresponding **val_loss** results for each model:

Table 3. Training result for each model

Dataset	Timesteps	Units	Epochs	Lowest val_loss
Daily	120	32	50	0.000027164696803083643
Weekly	60	50	100	0.00015265439287759364
Monthly	6	50	100	0.0008440767996944487

These results illustrate the parameters used for each dataset, along with the corresponding lowest and highest **val_loss** values obtained during model training.

Upon model construction, it undergoes evaluation using the test dataset. Evaluation of the daily test dataset with the corresponding daily model yields a Mean Squared Error (MSE) of 452.2284140627481 and a Root Mean Squared Error (RMSE) of 21.26566279387379.

Table 4. The variance between the actual and predicted values in the daily model

Date	Real Price	Predicted Price
2019-03-28	1295.15	1325.694702
2019-03-29	1295.40	1310.905029
2019-04-01	1293.50	1311.709595
2019-04-02	1290.30	1309.536865

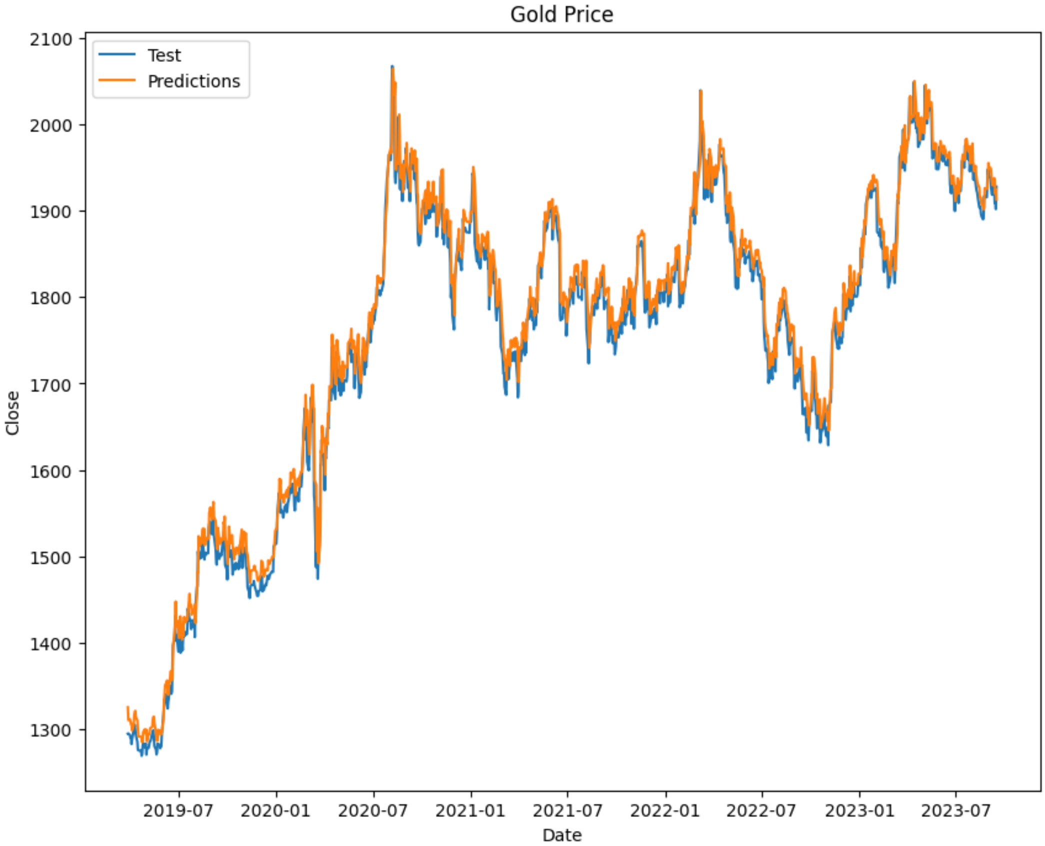

Figure 5. The graph showing the difference between the actual values and the predicted values in the daily model

Similarly, evaluation of the weekly test dataset with the corresponding weekly model reveals a Mean Squared Error (MSE) of 1346.1816584357384 and a Root Mean Squared Error (RMSE) of 36.69034830082345.

Table 5. The variance between the actual and predicted values in the weekly model

Date	Real Price	Predicted Price
2018-12-02	1252.6	1237.346680
2018-12-09	1241.4	1263.671265
2018-12-16	1258.1	1253.950073
2018-12-23	1286.1	1268.865723

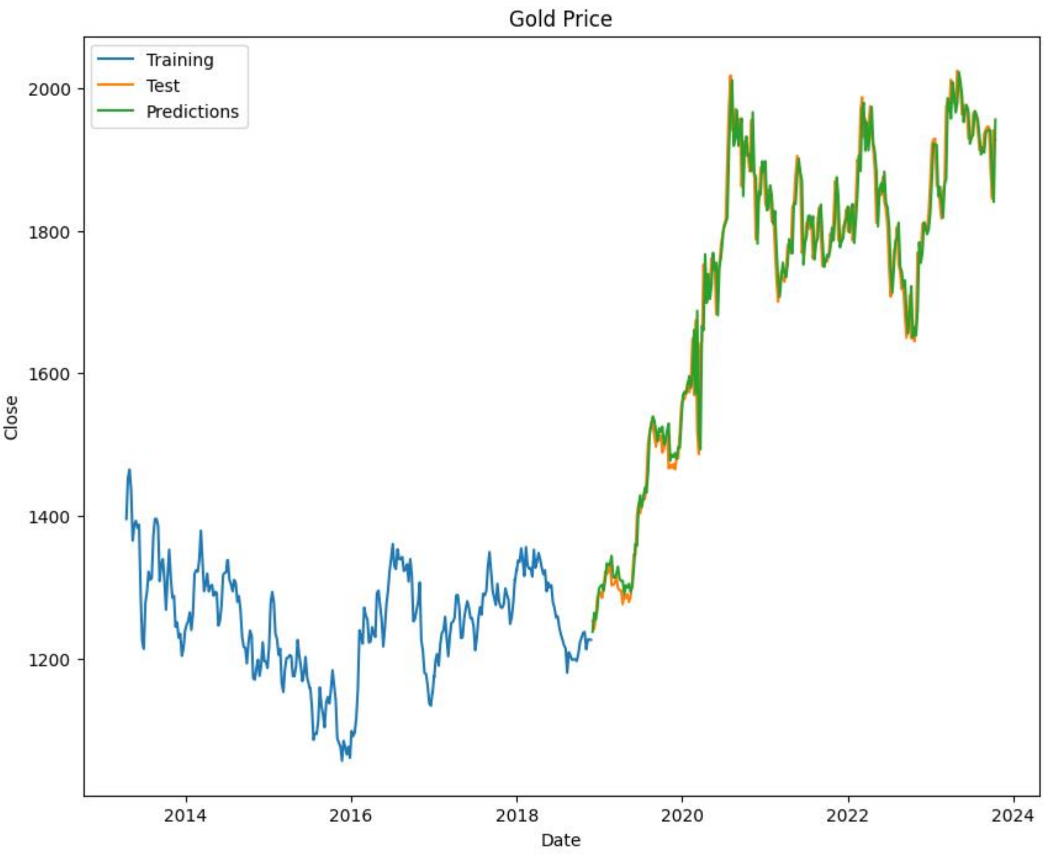

Figure 6. The graph showing the difference between the actual values and the predicted values in the weekly model

Furthermore, evaluation of the monthly test dataset with the corresponding monthly model yields a Mean Squared Error (MSE) of 11649.597907584808 and a Root Mean Squared Error (RMSE) of 107.93330305139747.

Table 6. The variance between the actual and predicted values in the monthly model

Date	Real Price	Predicted Price
2018-12-01	1287.70	1306.170898
2019-01-01	1331.60	1323.707397
2019-02-01	1322.70	1352.944580
2019-03-01	1304.50	1375.753784

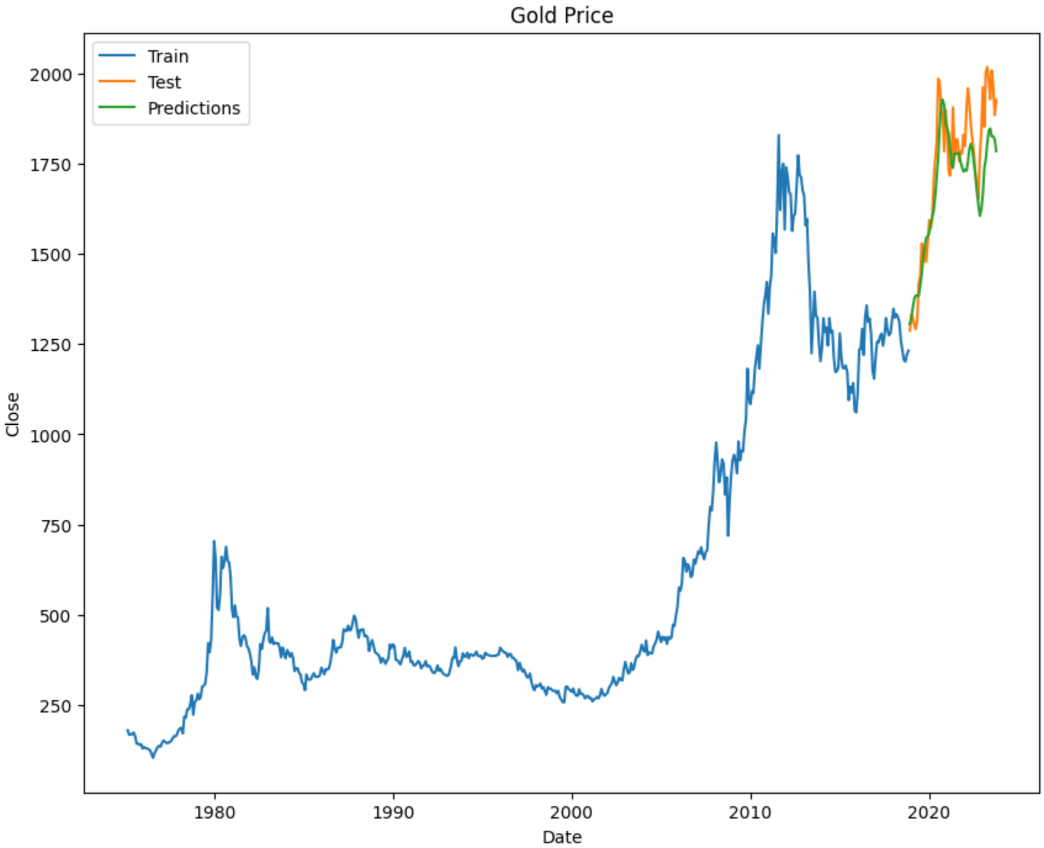

Figure 7. The graph showing the difference between the actual values and the predicted values in the monthly model

4. CONCLUSION

This study examines the prediction of gold price movements using Long Short-Term Memory (LSTM) models within a time series analysis framework. The research findings highlight the success of LSTM models in accurately forecasting gold price movements, particularly on daily and weekly timeframes. The daily model achieves a MSE of 452.23 and RMSE of 21.27, while the weekly model achieves a MSE of 1346.18 and RMSE of 36.69, indicating their strong adaptability to price changes. However, the monthly model performs less optimally with a MSE of 11649.60 and RMSE of 107.93.

Furthermore, analysis of the best-performing models reveals the influence of historical gold prices over specific time periods: 4 months for daily predictions, 15 months for weekly predictions, and 6 months for monthly predictions. This underscores the long temporal dependency in gold price movements.

This study acknowledges its limitations and suggests avenues for future research: 1) Exploring additional parameters like volume. 2) Integrating technical analysis indicators for a more comprehensive analysis. These refinements could enhance the accuracy and depth of the predictive models for forecasting gold price movements in future studies.

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