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Implementing LSTM models for forecasting gold prices and analyzing volatility

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Abstract

Stochastic volatility analysis is a sophisticated method for forecasting gold prices, accounting for the fact that volatility which is the degree of variation in gold prices is not constant over time but rather fluctuates unpredictably. This approach can be particularly effective because gold prices are often subject to sudden and unpredictable changes due to various economic, political, and market factors. Different statistical and machine learning models are available to predict the Gold price such as ARIMA, GARCH, SVM, Random Forest, GRU and CNN. In this paper LSTM model is implemented to forecast the Gold Price on the basis of 10 years of data from January 2013 to July 2023. Ater the implementation

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the value of Mean Absolute Error obtained is 1775.6294. In the future, this model can be extended to different versions of LSTM.

Subject Classification: *68T05.*

Keywords: *Gold Price, LSTM, MAE.*

1. Introduction

Gold, is well known for its diverse roles as a commodity, precious metal, and currency, has consistently drawn the interest of economists, investors, policymakers, and researchers globally. Its importance extends well beyond jewellery and adornment, significantly influencing industrial production [1]. To enhance the robustness of price data, [2] introduced a noise reduction technique based on wavelet transform, which effectively mitigates price volatility. This method is essential for improving the accuracy of subsequent predictions. Predicting the price of gold remains a critical concern for governments, scholars, and investors due to its multifaceted significance. Price fluctuations in mineral commodities, including gold, have a substantial impact on mineral investment decisions, affecting both mineral companies and resource-rich nations [3]. In today's global economy, accurately forecasting gold price movements is crucial for governments dependent on gold-based economies and for investors navigating the complexities of the commodity market. Zhao et al. [4] highlighted those fluctuations in commodity prices, including gold, are mainly driven by changes in oil prices due to the extensive use of crude oil as an energy source. The intricate price mechanism of international gold undergoes a complex cycle of fluctuations approximately every three months, influenced by various factors at different levels, such as oil prices, stock prices, and the US dollar exchange rate [5]. Gold price forecasting models aim to predict future gold prices by considering various factors and historical data. Various machine learning methods are applied to prediction of gold price such as ARIMA, SVM and LSTM. The LSTM model is employed in this paper to forecast the price of gold. In their research, [6] explore the field of predictive modelling by using an LSTM-P neural network model to estimate the values of gold and Bitcoin. A cornerstone of their method is the application of wavelet-based noise reduction, which significantly contributes to the enhanced accuracy of their predictions. By reducing high-frequency noise components effects on costs, they create a strong basis for more accurate predictions. In addition, the authors meticulously cultivate an enhanced LSTM forecasting model, denoted as LSPM-P [7]. This model undergoes training using historical price data encompassing both Bitcoin and gold, ultimately yielding highly accurate predictions of future prices. Their model's output is notable for its exceptional accuracy in predicting future price patterns. Notably, their LSTM-P model outperforms both traditional LSTM models and other time series forecasting methods in terms of accuracy and precision. Turning to the realm of stock market dynamics, [8] introduces a model and program designed for stock price prediction by harnessing data sourced from Yahoo Finance. The development of effective and precise stock price prediction systems is instrumental in assisting traders, investors, and analysts. These kinds of technologies offer insightful information on the future course of the stock market. Notably, Budiharto underscores the importance of utilizing short-term historical data for LSTM models to achieve optimal accuracy in stock price prediction. This insight supports to the growing collective knowledge surrounding predictive modeling in financial markets.

In a different study, [9] compared traditional time series models and deep learning algorithms for gold price prediction. They developed an ARIMA model to predict Indian gold prices using daily data from 2016 to 2020 from the World Gold Council. Their ARIMA (2,1,2) model shown the least AIC values among the models considered. In parallel, they investigated the predictive capacities of MLP, CNN, and LSTM models to forecast gold prices in India. Performance evaluation criteria such as mean absolute error, mean absolute percentage error, and root mean squared error were used to assess these models' forecasting abilities. As a result, the LSTM model outperformed the other three models in terms of predicting Indian gold prices.

The major contribution of this paper is a follow

- To study intends to compare the forecasting performance of LSTM to determine which method is more effective in predicting gold prices
- To Extend the forecasting horizon to cover the next ten years, enabling forward-looking predictions that offer insights into long-term price trends

2. Materials and Methods

To find out how macroeconomic uncertainty affects long-term gold futures volatility; this study uses a quantitative research design. The research design involves the use of the LSTM model. The Long Short-Term Memory (LSTM) model, proposed by [10], is another predictive model employed in this study. Time series data can be effectively analyzed using recurrent neural networks, especially Long Short-Term Memory (LSTM) networks, to identify patterns and relationships. The LSTM model is implemented using Python, a popular programming language for deep learning and artificial intelligence.

2.1. *Data Collection*

The main data used in this study is the global gold price data, which has been collected daily from January 2013 to July 2023 [11]. The data was sourced from Yahoo datasets, ensuring a wide range of observations over an extended period.

2.2. Data Preprocessing

To maintain data quality and consistency, comprehensive preprocessing is conducted before the data is fed into the models. This involves handling missing values, standardizing the data, and aligning the frequency of the macroeconomic variable with the daily gold price data.

1.3. *Model Evaluation and Analysis*

To evaluate the model's efficacy, a few appropriate statistical measures are employed: Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), and Mean Squared Error (MSE). The comparison of model performance will provide information on each model's efficacy in forecasting gold futures volatility under the influence of macroeconomic uncertainty.

3. Empirical Results & Discussions

The results shown are from fitting LSTM model to forecast the gold price. The graph shown in figure 1 shows the gold price trends throughout time, the x-axis showing the dates and the y-axis showing the closing prices by using the "matplotlib" library. The line that connects the points on the graph represents the trend of gold prices over time. If the line is generally moving upward, it indicates an increasing trend in gold prices.

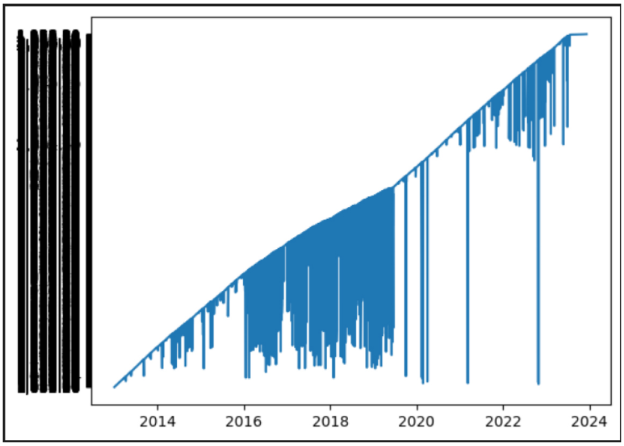

Figure 1

Trend of LSTM Gold Price.

Then data is categorised into training, validation and testing for LSTM model using "Numpy" library for predicting gold prices based on historical data. Graph in figure 2 allows to visually assess how well the dataset is split and whether any patterns or anomalies are present in the target values for each set. As the model is trained using the training data, the loss is displayed on the training loss curve. The model's loss as determined by applying the validation set of data is shown on the validation loss curve. The test loss curve displays the model's loss as it is assessed using the test set of data. The training loss is shown to be

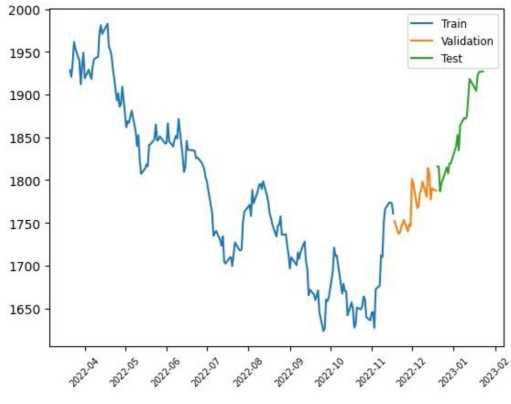

Figure 2

Line graph showing Train, Validation & Test

decreasing gradually over time in the graph, indicating that the model is becoming more proficient because of learning from the training set. The validation loss gradually drops over time, while not declining as swiftly as the training loss. It is possible that this means the model is beginning to overfit the training set. The test loss slightly increases when the validation loss reaches a plateau, suggesting that the model might be overfitting the training set and undergeneralizing to new data.

The author created, compiled, and trained a Sequential model using TensorFlow/Keras for forecasting using an LSTM network. It displays the mean absolute error (MAE) and loss for the training and validation sets for every epoch. The output illustrates how these metrics change as the model's training progresses. The goal is to observe a decreasing trend in the loss and MAE, which indicates that the model is improving its ability to match the data. At the end of training, author have a trained model that make predictions using the LSTM architecture for forecasting based on historical data. On the validation set, the model produced a mean absolute error (MAE) of 1766.03. This indicates that there was an average difference of 1766.03 units between the data that really occurred and the predictions made by the model. Table 1 displays the LSTM model's MAE [12] [13] [14].

The graph in Figure 3 created using Python shows the number of training predictions, validation predictions, and testing forecasts over time. The graph indicates that the number of training predictions increased steadily over time, while the number of validation predictions and testing predictions remained relatively constant. The graph shows that the number of predictions peaked in February 2023, and then began to decline. This may be due to several factors, such as the model becoming less accurate over time, or the availability of new data that the model was not able to learn from.

Overall, the graph provides a good overview of the performance of the model over time. It demonstrates that the model did not overfit the training data, but rather that it was able to learn from the data and get better at making predictions over time. The decline in the total predictions in February 2023 may be a cause for concern, but it is important to

Table 1

Mean absolute error (MAE) for both the training and validation.

Mean Absolute Error	Val Loss	Val Mean Absolute Error
1775.6294	3119434.2500	1766.0256

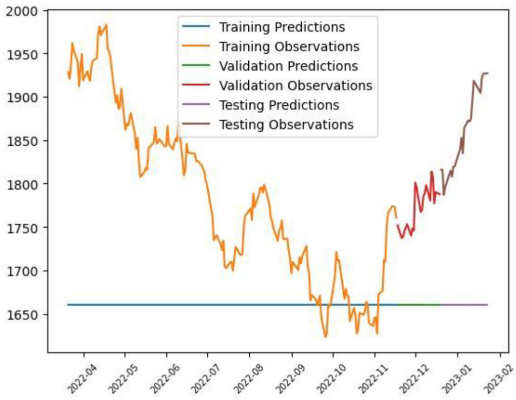

Figure 3

Predictions: Line Chart

investigate the reasons for this decline before making any conclusions. Every time, there are more training predictions made than testing and validation forecasts combined. This is so that the testing and validation data may be used to assess the model's performance after it has been trained using the training data. The number of validation predictions is typically close to the number of testing predictions. This ensures that the model's performance can be assessed objectively using the testing data, while the validation data is utilized to fine-tune the model's parameters.

The graph in Figure 4 shows the predictions of a machine learning model for a time series dataset. The training predictions are shown by the

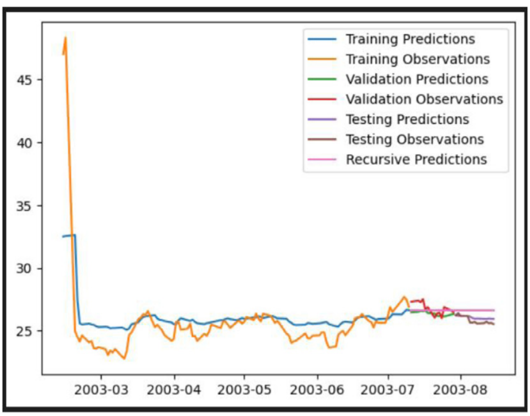

Figure 4

Predicted Model

blue line. The validation predictions are represented by the green line. The testing predictions are indicated by the orange line. The recursive forecasts are displayed with the red line. The actual values are represented by the black line. The training predictions are the closest to the actual values. This can be attributed to the model's acquisition of pattern recognition skills through training on the training set of data. The training predictions are generally more accurate than the validation predictions. This is because the model is less familiar with the patterns in the validation data, as it has not encountered it during training.

The testing predictions are less accurate than the validation predictions. This is because the testing a collection of data that the model uses has never observed previously, so it is not able to make any predictions based on its knowledge of the patterns in the data. The recursive predictions are less accurate than the testing predictions. This is because the recursive predictions are made on new data, using the model's own predictions as input. This means that the model's errors are compounded over time, resulting in less accurate predictions. Despite the errors, the model's predictions are accurate.

4. Conclusion

In line with our exploration and comparison of various conditional variance models, the primary This study's goal was to understand the complex dynamics of financial time series data for 10 years. Furthermore, our exploration of the LSTM model's potential in predicting gold prices opens a new avenue of research. While the model demonstrated strong predictive capabilities and a propensity to generalize well, it revealed certain periods of prediction decline. Addressing these issues is paramount to ensure the model's reliability for accurate gold price predictions. This aligns with our broader objective of enhancing predictive accuracy within the complexity of financial markets, where external factors wield significant influence.

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Conflicts of Interest

The authors declare no conflicts of interest.

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