Gold Price Prediction using Deep Learning Techniques.

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***Abstract*—Gold has always been the traditional store of value and medium of exchange. Predictions for the rate of gold in India by 2023 were estimated to be approximately Rs 68,000. If predictions about the gold price are right, investors will be able to determine when they should buy or sell the commodity. Gold price relates directly to the currency of the country and has a deep influence on the stock price; more importantly, a downturn in stock price is quite often associated with an upsurge in gold price. This paper aims at developing an early warning model on predicting the price of gold based on advanced techniques of deep learning involving LSTM, GRU, and RNN. These are compared with the widely used Linear Regression algorithm. Our results show that the deep learning techniques outperformed Linear Regression by a significant margin and achieved accuracies of 96% for each of the deep learning models. Hence, these gold price forecasting models using these advanced techniques give timely gold price predictions to investors for timely investment decisions resulting in appropriate buying and selling opportunities at the optimal price.**

Keywords— Prediction, MAPE, LSTM, GRU, RNN, Linear Regression, MAE, RMSE.

I. Introduction

The price of gold is an important constituent of the economic and financial scenario of banks and the stock market. Changes in the gold price have furthered the risk element of investment, which increases as the root causes behind this change are immensely complicated and caused by numerous factors. Even when the economic melt down hit the world in 2008, the price of gold remained hovering at a high peak. By and large in the history of the market, the ability of gold to become a safe haven and with sufficient liquidity, has generally attracted a large number of financial experts and gurus into it . A fractional change in the price of gold can end up resulting in significant profits or immense investment and economic losses. Beside this, the change in gold price has much impact on the gold mining companies due to the cost for their mining venture may become unviable if the future price of gold has drastic decreasing. The gold price prediction would help the financial investors and central banks to make appropriate decisions regarding their investment plans and manage the potential risks. However, it's hard to attain the ideal prediction of the gold price.

Though much significant gaps still exist in the literature on the subject of commodity price prediction, especially in the case of gold prices; the first paper on the subject, Commodity Price Prediction Using Long Short-Term Memory Algorithm, pointed out that the noninclusion of real-time data leads to a reduced precision level for predictions in dynamic markets Shashikant Suman et al[3]. This argument also indicates underutilization of alternative algorithms in machine learning besides failing to account for comprehensive strategies of risk assessment. Moreover, the study carried out in terms of market volatility impact was also limited, and external factors in economics and economics-the geo-political activities as well as macroeconomic indicators-were not accounted for. Such shortcomings are therefore a need to be filled to enhance effectiveness of LSTM models within commodity price prediction.

In the case of the second paper, Gold Price Prediction based on Yahoo Finance data using the LSTM algorithm, there are also some significant flaws. Other predictive models that can make the robustness of the prediction much better are not taken into consideration, and exhaustively analyze external economic factors responsible for gold price movement, thereby diminishing the applicability at context Windha Mega Pradny et al[1]. Other key points that would make the difference in predictions are that it does not provide real-time application of data, which affects accuracy in a fast-moving market. More importantly, there is no discussion on how model scalability may be achieved in dealing with large datasets and sensitivity analysis on choices of hyperparameters, which limits the understanding of how parameters affect model performance.

Another work on deep learning for gold price prediction explains that there is so much underexplored potential of deep learning algorithms in this domain since several studies to date remain dependent on classical machine learning methodologies Preeti R Prajapati et al[9]. Significantly, the previously suggested variants of long short-term memory models could improve accuracy and robustness in the prediction. Such research areas can help raise the effectiveness of methods used to predict a gold price.

The study on a data-based deep learning-based cryptocurrency price prediction model with particular indication of various limitations lists one of its critical weaknesses as: "No comparison for the performance with existing prediction methods" thereby increasing the arduousness in estimating the capability of the model GYEONGHO KIM al[6].Different types of input data make comparative analysis impossible, and an estimation of the performance of the model becomes complicated. In addition, the research study does not propose a unified framework that collates multiple sources of data for enhanced robustness and accuracy in the prediction of cryptocurrency prices. Therefore, filling these gaps is necessary to strengthen the study and give a comprehensive understanding about the dynamics of cryptocurrency prices.

In short, exploration of such gaps in existing literature is required to enhance the methods undertaken to predict the gold prices and support the decisions of financial investors and also central banks. As long as the challenge faces the task regarding the correct prediction of gold prices, the need for a more comprehensive approach involving real-time data, alternative models, and deeper analysis of the influencing factors will prevail for effective forecasting and risk mitigation.

II. Proposed Framework

A. Dataset

The dataset that was utilized in this study represented the daily gold prices from 2013 to 2023. The data were split into two sets: a training set and a testing set for this experiment. The training set consisted of daily gold prices from January 2013 to December 2021, amounting to nine years. This long time period ensures sufficient data for training the models and hence allows them to learn long-term, short-term trends and impart a rich understanding of numerous fluctuations in the gold market. fig. 1 illustrates the daily gold prices, providing a visual representation of the price trends and the split of training and testing data.

In addition to this, this transformation with natural logarithm, ln was used on both the training and testing dataset. This transformed data homogenized the variability within the data, stabilized patterns to it, as well as reduce any exponential trends that may be present in the data. Consequently, models are therefore more robust to tackle the price volatility naturally associated with gold prices and consequently improve their ability to capture the trend underlying from such series. The research work applies open-source libraries, including Pandas, NumPy, Keras, and TensorFlow. The algorithm has been programmed using the Python programming language. In this research the dataset contains 2,584 rows and has the following relevant characteristics: open, close, high, low prices, volume, date, and percentage change. It splits the data into 80% training and 20% testing to actually train the model and evaluate it.

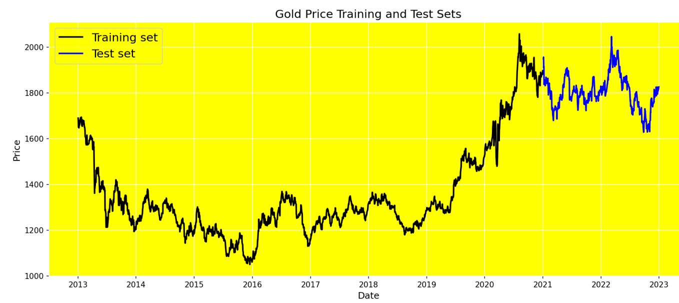

Fig. 1. Daily gold price trend from 2013 to 2023

B. Architecture of the Framework

The detailed architecture of the proposed methodology is represented in fig. 2.

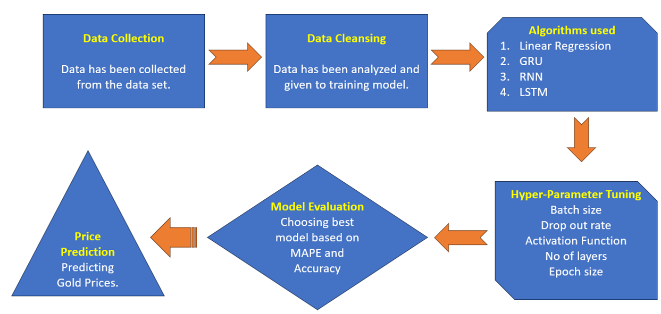

Fig. 2. Proposed Methodology Framework

A preprocessing step is conducted on the data extracted from Kaggle, identifying missing or null values that require proper handling. As a result of the cleaning stage, the datasets are divided into training and testing datasets, which can be used in training several deep learning models. It would make up for several parameters in hyper parameter tuning, further improving model performance. The models are ranked using metrics like Mean Absolute Percentage Error (MAPE), Loss, Root Mean Square Error (RMSE), and Accuracy. The model that would best perform those metrics will be used for gold price prediction.

C. Algorithms Used

The aim of this study is to forecast gold prices using regression algorithms and recurrent neural networks (RNNs). We employ Linear Regression, Gated Recurrent Units (GRU), Long Short-Term Memory (LSTM), and RNN to predict gold prices and compare their performances.

1) Linear Regression: The relationship is expressed as:

$$Y = a + bX + e$$

- X is the predictor variable used for making predictions.
- Y is the criterion variable that is being predicted.
- a represents the intercept, b is the slope, and e is the error term.

2) Gated Recurrent Unit (GRU): The GRU architecture simplifies LSTM by combining the forget and input gates into a single update gate, allowing the model to maintain long-term dependencies more efficiently. The updates for the GRU are given by:

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r)$$

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z)$$

$$\hat{h}_t = \tanh(W_h \cdot [r_t * h_{t-1}, x_t] + b_h)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \hat{h}_t$$

Where:

- r_t is the reset gate.
- z_t is the update gate.
- $\hat{h}_t$ is the candidate hidden state.
- h_t is the hidden state at time t.

3) Recurrent Neural Network (RNN): The RNN uses recurrent connections to process sequences of data, enabling it to maintain a memory of previous inputs. The update for the hidden state is defined as:

$$h_t = \Phi(W_h h_{t-1} + W_x x_t + b_h)$$

Where:

- x_t is the input at time t.
- W_h and W_x are weight matrices for the hidden state and input, respectively.
- b_h is the bias term.

4) Long Short-Term Memory (LSTM): The LSTM architecture includes a forget gate, input gate, and output gate to regulate information flow. The forward pass of an LSTM unit with a forget gate is expressed as:

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

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i)$$

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

$$c_t = f_t * c_{t-1} + i_t * \tanh(W_c \cdot [h_{t-1}, x_t] + b_c)$$

$$h_t = o_t * \tanh(c_t)$$

Where:

- f_t is the forget gate.
- i_t is the input gate.
- o_t is the output gate.
- c_t is the cell state.
- h_t is the hidden state.

III. MODEL TRAINING AND EVALUATION

In this section, we evaluate the predictive power of three deep-learning models-LSTM, GRU, and RNN-regarding gold price predictability as compared to actual values. The performance of each model can be analyzed on the basis of various metrics. Metrics will enable us to analyze accuracy and errors of the models in predicting future gold prices.

The following figures are the comparison in visuals for actual gold prices and predicted ones based on the actual model and forecasted values over the test data.

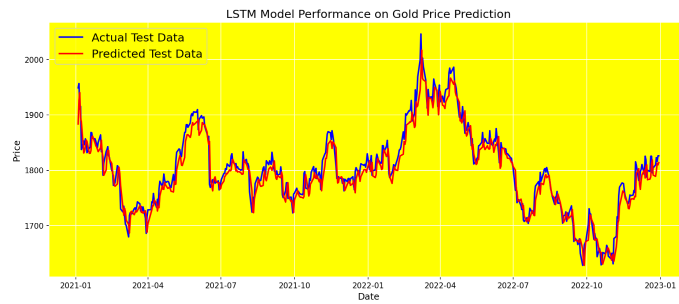

Fig. 3. Prediction performance of the LSTM model

fig. 3 shows the prediction performance of the LSTM model. The trend provided by the LSTM model of gold prices has been pretty effective, as the values of actual and predicted have almost reached each other. In this way, it points out that there is good modeling potential of the given time series data with the LSTM since it is able to retain long dependencies.

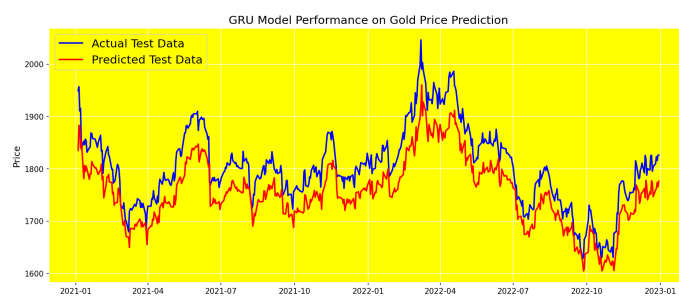

Fig. 4. Performance of the GRU model

fig. 4 illustrates the GRU model performance. From the figure, it is clear that the GRU model captures the overall trend of the data but at times makes some minor departures between its predicted values and the actual values. However, the GRU model is a strong predictor and also provides competitive results relative to the LSTM model.

fig. 5 depicts the performance of the RNN model. It can be observed that although the overall trend with which the RNN model captures the dynamics of gold prices is highly effective, it varies more and is less precise compared to the LSTM and GRU models. This is because the RNN has a less complex architecture and fails to track long-term dependencies of time series data.

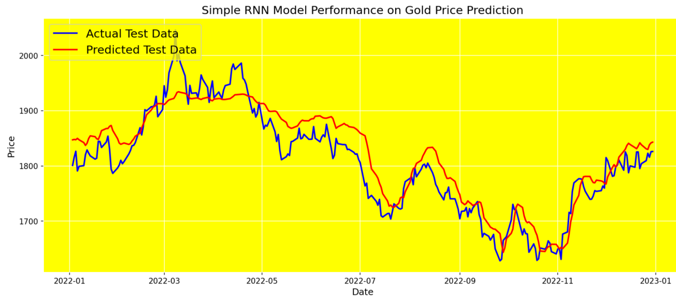

Fig. 5. Performance of the RNN model

Regarding performance measures, the LSTM model showed better performance than those of GRU and RNN in relation to MAPE, RMSE, and MAE. The lowest MAPE and RMSE were obtained by the LSTM model, respectively, which means higher accuracy with lower error in the case of its predictions. The performance follows by GRU and the errors are relatively much higher, even in the case of the time series developed from RNN.

Overall, the deep learning model acquires more overall benefits compared to the traditional approaches like Linear Regression concerning the existing complexities and dependencies in the temporal patterns of the gold price data. The results obtained showed some promise in making the LSTM and GRU models use historical data to a certain extent; therefore, the predictions made were more accurate. Improvement can also be achieved by adding new features and also by the use of hybrid architectures to catch the contribution of other factors that have an impact on the gold prices.

IV. Results

A. Model Performance Metrics

The performance of the models was evaluated based on test loss, Mean Absolute Percentage Error (MAPE), and accuracy. The results are summarized in Table I.

TABLE I
Model Performance Metrics

Model	Test Loss	Test MAPE	Test Accuracy
GRU	0.00254	0.06183	0.93817
Simple RNN	0.02739	0.19777	0.80223
LSTM	0.00038	0.01998	0.98002

B. Discussion of Findings

- **LSTM Performance**: The LSTM model achieved the lowest test loss of 0.00038 and the highest accuracy of 98.00%. The MAPE of 0.01998 indicates that LSTM is particularly effective at minimizing the percentage error in predictions, making it a strong candidate for gold price forecasting.
- **GRU Performance**: The GRU model also performed well with a test loss of 0.00254 and an accuracy of 93.82%. Its MAPE of 0.06183 suggests it is a reliable alternative but less effective than LSTM in capturing the underlying patterns in the data.
- **Simple RNN Performance**: In contrast, the Simple RNN model exhibited the highest test loss of 0.02739 and the lowest accuracy of 80.22%, with a MAPE of 0.19777. This indicates that the Simple RNN struggled to learn the time dependencies effectively, leading to poorer predictive performance compared to the other models.

C. Visual Comparisons

Figures 3, 4, and 5 illustrate the actual gold prices against the predicted prices for the LSTM, GRU, and Simple RNN models, respectively. These visual representations further emphasize the superior performance of the LSTM model.

To provide a comprehensive evaluation of the models, we present two additional figures.

In fig. 6, two further figures, which indicate a more comprehensive model analysis, are available.

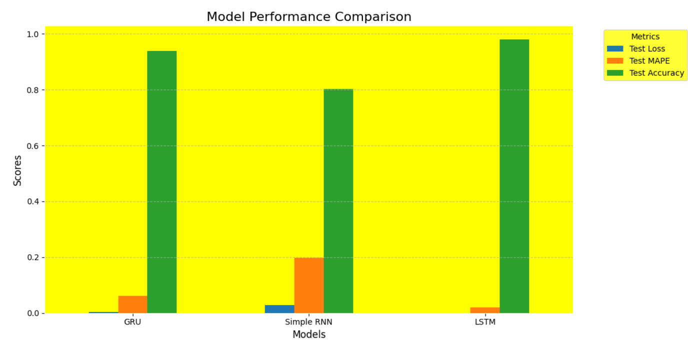

Fig. 6. Diverse performance metrics, including MAPE loss and accuracy, for the LSTM, GRU, and Simple RNN models. This demonstrates how each model serves under different metrics while highlighting strengths and weaknesses in the nature of each architecture.

fig. 7 is a zoomed version of the accuracy of the models alone. Accuracy scores achieved by both LSTM, GRU, and Simple RNN models are graphically presented to enable them to come into better focus for higher predictive ability.

V. Conclusion

In fact, the strength of the proposed model will come from a comparison in task performance of different models of deep learning, such as GRU, RNN, and LSTM, with the classical approach of Linear Regression. Deep models attempt to grasp complex patterns or relationships that could exist nonlinearly in time series data, which makes them superior for applications, such as predicting gold prices. In the current work, the evaluation was mainly based on Mean Absolute Percentage Error (MAPE), which highlights the capability of predictive models through measuring the error as a percentage of actual values.

In the results, the deep learning models have outperformed the Linear Regression model in predicting gold prices, showing their strong ability in capturing time dependencies and complex interactions in the data. Among these are LSTM and GRU, which are particularly suited for learning from long

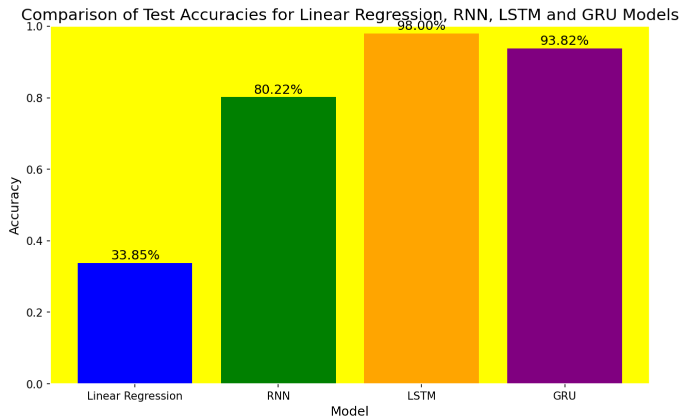

Fig. 7. Accuracy comparison of Linear Regression, RNN, LSTM and GRU models, emphasizing the superior accuracy of the LSTM model in discovering actual trends in gold price data.

sequences of historical data, as they were designed to keep track of long-term dependencies and overcome the limitations of traditional models and basic neural networks. This enables them to model sequential data effectively, making them highly suitable for time series forecasting tasks such as gold price prediction.

However, there is still no definitive or optimal solution for accurately forecasting gold prices, despite the strong performance of deep learning models. This is largely due to the fact that gold prices are highly influenced by a wide range of external factors such as geopolitical events, economic indicators, inflation rates, currency fluctuations, and even market sentiment, which are difficult to model comprehensively. These external factors introduce significant uncertainty and volatility into the prediction process, making it challenging to capture all relevant influences through any single model, no matter how sophisticated.

Furthermore, the dynamic nature of the gold market means that models need to constantly adapt to changing conditions. While deep learning models provide a promising approach by leveraging historical data patterns, they are still limited by the availability and quality of data, as well as the unpredictable influence of certain external factors that cannot be fully captured in a dataset.

In conclusion, although the deep learning models developed in this study demonstrated clear advantages over Linear Regression in predicting gold prices, the inherent complexity and unpredictability of the gold market remain significant challenges. Further research and model development, potentially incorporating additional external factors and more sophisticated architectures, will be necessary to improve the robustness and accuracy of gold price forecasts in the future.

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