Predicting monthly gold prices in indian rupees using ARIMA, LSTM, GRU, and Simple Linear Regression models

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Abstract: For investors and financial analysts to make informed decisions, having precise forecasts of gold prices is crucial. This study examined the effectiveness of various time series models in predicting gold prices in Indian Rupeea variety of models, ranging from linear models like Auto Regressive Integrated Moving Average (ARIMA) and Simple Linear Regression, to more complex nonlinear models such as Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) were utilised. In the study, a statistical technique was used to analyse the data collected over a twenty-year period, from January 2001 to December 2019. RMSE and MAPE were used to evaluate the models' performance. The Simple Linear Regression model achieved an RMSE value of 834.67 and a MAPE value of 2.22%, demonstrating its superior performance compared to the other models. The LSTM and GRU models achieved RMSE values of 1160.5 and 1214.8, respectively, suggesting comparable levels of performance. The MAPE values of the LSTM model and the GRU model differed by 2.96%, with the latter being 2.83%. On the other hand, the ARIMA model had a MAPE value of 22.9% and an RMSE value of 7121.1, which was noticeably lower than the previous model. Moreover, the results showed that both LSTM and GRU have the ability to capture non-linear correlations in the fluctuations of gold prices.

Keywords: Gold Price, ARIMA, RNN, LSTM, GRU, univariate time series.

1. Introduction

Gold, a precious metal that has a rich historical meaning that spans centuries, has not only been used as a form of cash but also as a prominent investment commodity. This is because gold has a rich historical significance. The dynamics of its prices are impacted by a wide variety of factors, including swings in the economy and geopolitical tensions, as well as supply and demand dynamics. The precise forecasting of gold prices is of tremendous significance to investors, financial experts and traders alike because of the central position that gold plays in investment portfolios. Decision-makers are given the ability to strategically time their gold transactions and design trading strategies that are successful as a result of such expectations. The purpose of this research was to evaluate the accuracy of a number of different forecasting models in terms of their ability to anticipate monthly gold prices that are denominated in Indian rupees. For the purpose of comparison, two linear models, namely ARIMA and Simple Linear Regression, were compared to two nonlinear models, namely LSTM and GRU. This investigation, which was conducted using a univariate methodology, which is based purely on historical price data, intended to determine the strengths and shortcomings of each model in terms of its ability to capture the dynamics of gold prices.

In spite of the fact that they are extensively utilized, traditional forecasting approaches such as ARIMA frequently struggle to adequately capture the intricacies of time series data such as gold prices. This is because the fundamental assumption of these techniques is that the data will be linear. Taking into consideration the complex nonlinear interactions that are inherent in the fluctuations of the gold price, this restriction becomes readily obvious. On the other hand, nonlinear techniques like as machine learning and deep neural networks, which are illustrated here by LSTM and GRU models, have the potential to show promise; yet, they may display unpredictability in performance and struggle to properly contain the complexity of gold price behavior.

Using ARIMA, LSTM, GRU, and basic linear regression models, various research publications have focused on predicting monthly gold prices in Indian Rupees. These models have been used to create the predictions. A comparison was made between the ARIMA and LSTM

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models and it was discovered that the LSTM model performed better than the ARIMA model in terms of accuracy, with an RMSE value of 8.124 and a MAPE value of 0.023 (Ferdinandus et al., 2023). Similarly, an analysis of the outcomes of the ARIMA and LSTM models' forecasting algorithms and discovered that there were inconsistencies between the point forecast and the actual gold return rate (Zhang, 2023). A comparison was made by Fang between three models, which included regression analysis, BP neural network, and time series analysis. He discovered that all three models possessed high levels of dependability and accuracy, but that they were better suited for short-term forecasts (He et al., 2019). ARIMA (0,1,2) was utilized in order to forecast daily gold prices and estimate the amount of error that existed between the observed values and the estimated values (Nallamothu et al., 2023). The significance of employing precise forecasting methods in order to make correct predictions regarding the price of gold has been emphasis (Khairil et al., 2023) They also addressed the utilization of ARIMA, LSTM, and basic linear regression models.

When everything was taken into consideration, the purpose of this research was to conduct a thorough analysis of the forecasting capabilities of each model. The objective was to determine which method, whether linear or nonlinear, provides the highest level of predicted accuracy for gold prices expressed in Indian rupees. A detailed investigation was implemented, making use of tools such as SAS Studio and JupyterLab (Zhang & Ci, 2020), with the goal of locating the model that is most compatible with the dynamic nature of gold price forecasting and that is capable of producing trustworthy predictions in the face of market volatility and uncertainty. The purpose of This endeavour was to provide stakeholders with insights that are essential for making informed decisions in the sphere of gold investment and trade. This was accomplished through the systematic examination of the accuracy of forecasts.

2. The adopted models

The adopted models for this research, namely ARIMA, LSTM, GRU, and Simple Linear Regression, were meticulously chosen to forecast monthly gold prices in Indian Rupees, ensuring a comprehensive analysis of both linear and nonlinear methodologies

2.1. ARIMA

ARIMA is a statistical model used to analyse and forecast time series data. It combines auto-regressive, integrated, and moving average components to provide valuable insights. It is represented linearly, illustrating the connection between past and future values. ARIMA models are defined by three parameters: p, d, and q. As explained in literature (Alsharef et al., 2022), the parameter p signifies the number of autoregressive terms (AR), the parameter d signifies the number of differencing terms (I), and the parameter q signifies the number of moving average terms (MA). These terms, represented by the abbreviation "AR," illustrate the influence of past values of the time series on the current value. Terms starting with the letter "I" indicate the level of differencing in the time series, suggesting that the series is modified to achieve a stationary state. Previous forecast mistakes have a notable impact on the current forecast, as demonstrated by the (MA) terms (Hung & Lee, 2022; Ospina et al., 2023). Here is the equation that represents the ARIMA components: Yt is the differenced data, c is the intercept, Yt−1 to Yt−p represents the lagged values, εt−1 to ε t−q represents the lagged errors (He et al., 2019). ϕ is the parameter of the autoregressive part of the model, and θ is the parameter of the moving average part (Ospina et al., 2023).

$$Y_t = c + \phi_1 Y_{t-1} + \phi_2 Y_{t-2} + \ldots + \phi_p Y_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t$$

(Hung & Lee, 2022; Ospina et al., 2023)

ARIMA Model requires the data to be stationary (Alsharef et al., 2022). In the real world, time-series data often exhibits non-stationary behaviour. The ARIMA model addresses this issue by employing a differencing transformation to convert non-stationary data into stationary data. This process entails substituting the values of time-series data with the disparities between these values and their respective values in previous time periods (Alsharef et al., 2022).

2.2. Simple Linear Regression

Statistical modelling involves establishing a linear relationship between a dependent variable and an independent variable. One technique that is commonly used is called simple linear regression. Understanding the equation of the line that best fits the data is a key goal of the Simple Linear Regression technique. This equation allows for predictions of the dependent variable based on changes in the independent variable. In the equation of Simple Linear Regression, the dependent variable is represented by y, while the independent variable is represented by x. Intercept and slope are commonly represented by the variables β_0 and β_1, respectively. This unexplained variation, which falls outside the scope of the model, is commonly known as the error term (Alsharef et al., 2022; Schreiber-Gregory & Bader, 2018).

$y = \beta_0 + \beta_1 x + \varepsilon$ (Mali, 2021)

During the process of time series analysis, the time itself serves as the independent variable. This allows for the identification of relationships, trends and patterns that occur over a period of time. This information is then utilized in order to develop predictions regarding the dependent variable. Certain assumptions concerning the relationship between the variables and the error terms need to be satisfied in order for the Simple Linear Regression technique to produce findings that are considered to be valid and accurate. They include the linear relationship that exists between the variables that are dependent and those that are independent. It is also necessary that the observations contained in the dataset be independent of one another. The significance of this is that the value of one observation should not have any impact on the value of another observation. It is also important that the residuals have a normal distribution, and that the variance of the residuals remains the same across all levels of the independent variable (Schreiber-Gregory & Bader, 2018).

2.3. Recurrent Neural Networks (RNNs)

Recurrent neural networks are a type of neural network that excel at handling sequential data, such as data organised in a time series. Residual neural networks (RNNs) have the remarkable ability to capture temporal connections between inputs, unlike feed-forward neural networks that treat each input in isolation. Various tasks, such as speech recognition, natural language processing, machine translation, and time series forecasting, can greatly benefit from their application (Zargar, 2021).

2.3.1. Long Short-Term Memory Networks (LSTM)

Long Short-Term Memory Networks are a variant of Recurrent Neural Networks that employ a specialised memory cell to retain information over extended durations. Just like a neuroscientist, we can observe that this memory cell is governed by a series of gates that regulate the flow of information in and out of the cell. The LSTM block is a crucial element of the LSTM unit. Understanding the functioning of the forget gate involves analysing which information is selected for retention and which is discarded from the previous cell state. The input gate is responsible for determining which new information should be incorporated into the cell state. Understanding the cell state is crucial for comprehending how information is stored and retained over time. Understanding the role of the output gate is crucial in determining which information from the cell state is selected for output (Zargar, 2021). The cell state is updated by considering the forget and input gates (Thakur, 2018). Below equations are for LSTM gates (Ospina et al., 2023), where f_t, i_t, and o_t are forget, input and output gates. x_t is the input at time t. σ, and $\tanh$ represent sigmoid and hyperbolic tangent activation functions to output values between 0 (to forget) and 1 (to remember). W, U, and b represent the weights of the input and recurrent connections, and biases for gates. C_t is the current memory cell state and $\tilde{C}_t$ is the candidate cell state at time t. h_t is the hidden state which is the output of the LSTM cell at time t. h_{t-1} is the output from the previous time step t-1 (Mateus et al., 2021).

$$f_t = \sigma(x_t W_f + h_{t-1} U_f + b_f)$$

$$i_t = \sigma(x_t W_i + h_{t-1} U_i + b_i)$$

$$o_t = \sigma(x_t W_o + h_{t-1} U_o + b_o)$$

$$\tilde{C}_t = \tanh[(x_t W_c + h_{t-1} U_c + b_c)]$$

$$C_t = \sigma(f_t \times C_{t-1} + i_t \times \tilde{C}_t)$$

$$h_t = tanh(C_t) \times o_t$$ (Mateus et al., 2021).

2.3.2. Gated Recurrent Units (GRUs)

GRUs offer a more streamlined architecture in comparison to LSTMs, featuring a reduced number of gates and quicker processing. The GRU block utilises the update gate to regulate the flow of information in and out of the cell state. This gate determines which information is retained from the previous cell state and which information is added as new. Understanding the reset gate is crucial in determining the extent to which past information is forgotten (Mateus et al., 2021). Although GRUs are more computationally efficient than traditional RNNs, they may not be as proficient as LSTMs in capturing long-term dependencies in sequential data (Zargar, 2021). Below are the equations for the gates in a GRU model. The update gate is denoted as z_t, while the reset gate is denoted as r_t. The weight for input x_t is represented by W_z, W_r, and W. The weights of the previous time step are represented by U_z, U_r, and U. b_r, b_z and b are biased. The sigmoid and hyperbolic tangent activation functions, σ and tanh, respectively, are used to produce output values ranging from 0 (indicating forgetting) to 1 (indicating remembering). The hidden state at time t is denoted as h ̃_t, while h_(t-1) represents the hidden state at the previous time step (Ospina et al., 2021).

$$z_t = \sigma(x_t W^z + h_{t-1} U^z + b_z)$$

$$r_t = \sigma(x_t W^r + h_{t-1} U^r + b_r)$$

$$\tilde{h}_t = \tanh[(r_t \times h_{t-1} U + x_t W + b)]$$

$$h_t = (1 - z_t) \times \tilde{h}_t + z_t \times h_{t-1}$$ (Mateus et al., 2021).

2.4. Models' performance metrics

Assessing the performance of predictive models is essential to guarantee their efficacy in practical scenarios. RMSE and MAPE are two commonly used measures in various fields. These performance metrics illustrate the discrepancy between the observed value and the projected value (Ospina et al., 2021).

Root Mean Square Error (RMSE) quantifies the average magnitude of the discrepancies between anticipated values and actual values. It measures the total amount of error in the predictions. The equation below represents the relationship between the variables: n represents the number of observations, Yi represents the actual value, and Fi represents the projected value (Ospina et al., 2021).

$$\text{RMSE}=\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_i - F_i)^2}$$

MAPE quantifies the average discrepancy between predicted and actual values by representing it as a % of the actual values. This allows for a relative assessment of the accuracy of the predictions. The equation below represents the relationship between the number of observations (n), the actual value (Yi), and the predicted value (Fi) (Ospina et al., 2023).

$$\text{MAPE}=\frac{1}{n}\sum_{i=1}^{n}\left|\frac{Y_i - F_i}{Y_i}\right| \times 100\%$$

An indicator of a statistical model's goodness of fit is the Akaike Information Criterion (AIC). It satisfies both the need for a sophisticated model and the need for an explanation of the facts. According to Ospina et al. (2021), the AIC may be determined using the following equation: where k is the model's parameter count and L is the maximum likelihood function value.

AIC= $-2\log(L) + 2k$

The model that has the lowest AIC (Akaike Information Criterion) score is regarded as the most optimal model. Nevertheless, this ensures that the model is a more suitable match for the data. The study uses AIC to determine the optimal order (p, d, q) for the ARIMA model.

3. Dataset description

The dataset that was utilized for this investigation, was collected from the Kaggle website Agarwals. (2020). It is comprised of historical gold prices ranging from January 2001 to December 2019. There are two variables involved: the price of gold and the date. There is a record of the price of gold in Indian Rupees. The date is comprised of 228 monthly records on the price of gold over the course of fifteen years.

3.1. Dataset Pre-processing

The descriptive statistics of gold prices show a minimum value of 4267 and a maximum value of 38214. The skewness and kurtosis values describe the shape of gold price distribution. A skewness value of 0.0077 indicates that the distribution is very slightly skewed to the right. This means that the tail of the distribution extends more to the right than it does to the left. A kurtosis value of -1.6178 indicates that the distribution is platykurtic, meaning that the distribution has a lower peak and fatter tails than a normal distribution. Based on that, the gold price distribution is not normal. Many methods for normalizing non-normal data such as log, square root and inverse, have been attempted, but none have been successful with this variable.

4. Methodology

In order to guarantee reliability and precision in the process of predicting gold prices, the following technique was painstakingly implemented in the study: Collection of Data and Pre-processing: The research project gathered information on the price of gold and then proceeded to do a comprehensive pre-processing phase on it. It was necessary to clean the data in order to eliminate any inconsistencies or errors, and then transform it in accordance with the requirements in order to guarantee that it was suitable for analysis. Assessing Stationarity: In order to ascertain the intrinsic characteristics of the data, the stationarity of the data was critically examined. In the event that it was discovered that the data were not stationary, the proper steps were taken to transform it into a stationary form, which is necessary for the completion of time series analysis. The Selection of Models Using AIC: Through the utilisation of the Akaike Information Criterion (AIC), the research endeavoured to systematically determine the ARIMA model that was the most appropriate and effectively reflected the fundamental patterns and dynamics of the gold price in question. For the purpose of ensuring that the model is accurate and effective in forecasting, this phase is absolutely necessary.

In order to make the process of training and evaluating the model more manageable, the dataset was separated into separate training and testing sets. The models' performance on data that has not yet been observed can be evaluated in an objective manner thanks to this separation. The research investigation utilized a number of methodologies, such as ARIMA, Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Simple Linear Regression, in order to develop forecasting models. Every single model underwent painstaking optimisation by means of fine-tuning its hyperparameters in order to improve its predictive powers. Following the completion of the development process, the models were subjected to rigorous training on the training dataset in order to get an understanding of the underlying patterns and relationships that were present within the data. After that, the trained models were evaluated on the testing dataset in order to determine how well they performed and how well they could generalize those results.

A wide variety of performance metrics, including Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE), were utilized in order to conduct a complete evaluation of the accuracy of the models' forecasting capabilities. A better understanding of the models' capacity to reliably forecast gold prices throughout a variety of time periods can be gained through the utilisation of these measures. Identifying the Model That Performs the Best Based on the findings of the evaluation, the research determined which model exhibited the highest performance in terms of the accuracy and dependability of its forecasts. For the sake of making decisions and putting actual applications into practice, this stage is absolutely necessary for picking the most effective model.

5. Discussions and results

5.1. ARIMA model

Before applying the ARIMA model to the data, the data should be stationary. As appears in the ARIMA, there is an upward trend, and when a time series exhibits a trend, the stationarity assumption is not met. As per the Augmented Dickey-Fuller test result, the p-value is (0.9689) which is greater than alpha (0.05). This leads to accepting the null hypotheses of this test (the data is not stationary) Michalková & Pobočíková, (2023). According to this, differencing is necessary to be applied during the development the models. After testing order 1 and 2, the difference of order 2 (d=2) was sufficient to achieve stationary in the data.

After examining different models, three ARIMA models with varying (p, d, and q) parameter combinations were fitted to the data. The best fitting model is chosen according to the lowest value of Akaike’s Information Criterion (AIC). In Table 1, ARIMA (1, 2, 2) has the lowest AIC value, and it is chosen in this study to compare it with other methods.

Table 1. AIC results for ARIMA models

ARIMA (p, d,q)	AIC
(2, 2, 2)	3605.44
(1, 2, 2)	**3603.495**
(2, 2, 1)	3604.083

To check the if ARIMA model (1, 2, 2) fit the data, there are three stages for Box-Jenkins Modelling Methodology (Wang, 2008). They are identification, estimation and diagnostic checking, and then forecasting. To examine the model fitting, identification, estimation and diagnostic have been checked. In the identification stage, of autocorrelation check for white noise represents the p-value less than alpha (0.05), which leads to rejecting the null hypothesis, and conclude that the data is not white noise.

Moreover, by visually inspecting the Autocorrelation Function plot in Figure 1, it is noticeable that there are 25 lags. The spikes of lags 1, 9, and 10 are significantly different from 0. They reach beyond the shaded area that represents the 95% confidence intervals for each lag. This means that the data is correlated. The same conclusion demonstrated also by the partial autocorrelation function (PACF). It shows the correlation between the time series data and its lags after removing the effects of previous lags.

In the estimation and diagnostic checking stage, the maximum likelihood estimation lists four parameters in the model. It shows the estimated values of the parameters, the standard errors and t values for the estimates. Out of them, the AR (1) model (an autoregressive model of order 1) with its estimated value of -0.72826 fits the date, since its p-value is less than alpha (0.05) (see Table 2).

Correlations of Parameter Estimates shows no correlation relationships between the parameters that may influence the results.

Table 2. Simple Linear Regression model results

Number of Observations Read	228
Number of Observations Used	227
Number of Observations with Missing Values	1

Analysis of Variance					
Source	DF	Sum of Squares	Mean Square	F Value	Pr > F
Model	1	25619050247	25619050247	53771.3	<.0001
Error	225	107200107	476445		
Corrected Total	226	25726250354			

Root MSE	690.24990	R-Square	0.9958
Dependent Mean	18630	Adj R-Sq	0.9958
Coeff Var	3.70503		

Parameter Estimates					
Variable	DF	Parameter Estimate	Standard Error	t Value	Pr > |t|
Intercept	1	120.68391	92.03403	1.31	0.1911
Gold_Price_lag_1	1	1.00149	0.00432	231.89	<.0001

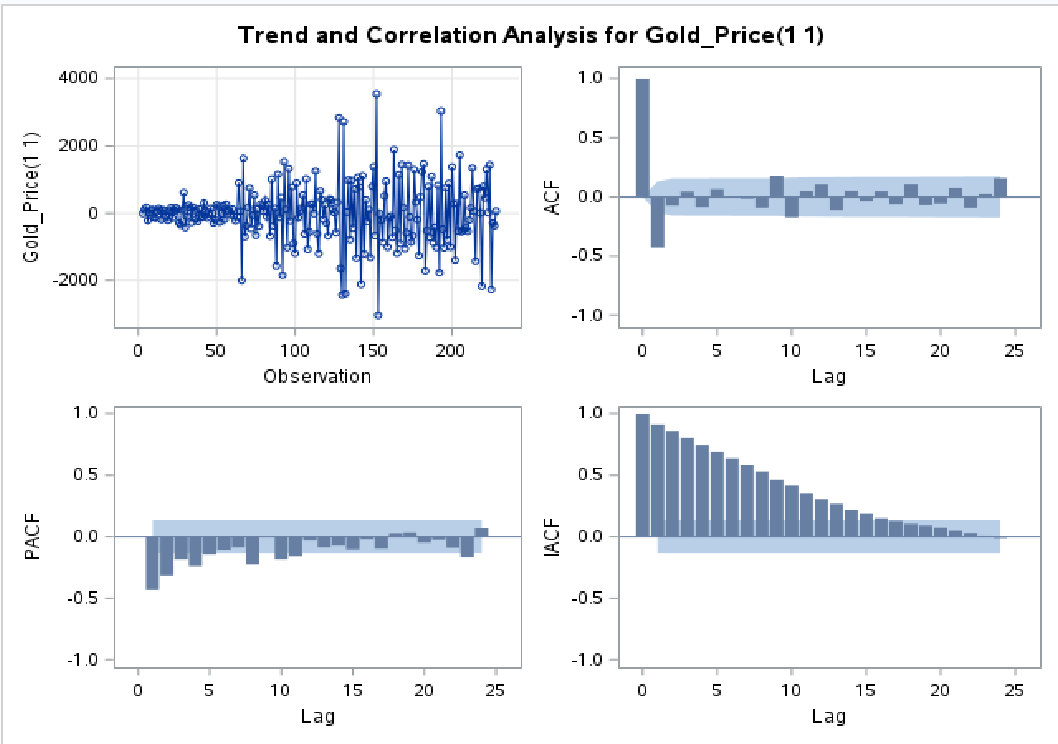

Figure 1. Trend and Correlation Analysis for gold prices

Based on Autocorrelation Check of Residuals, the p-value is greater than alpha (0.05) for all lags. This led to accepting the no-autocorrelation hypothesis in the residuals. According to that, there is no autocorrelation in the residuals, and they are white noise. This indicates that the AR (1) model is fully adequate for this data. In Figure 2, the plots of Residual Correlation Diagnostics for gold prices have been shown. The plot of Lag versus ACF shows all spikes of lags are significantly not different from zero, which proves the absence of autocorrelation in the residuals.

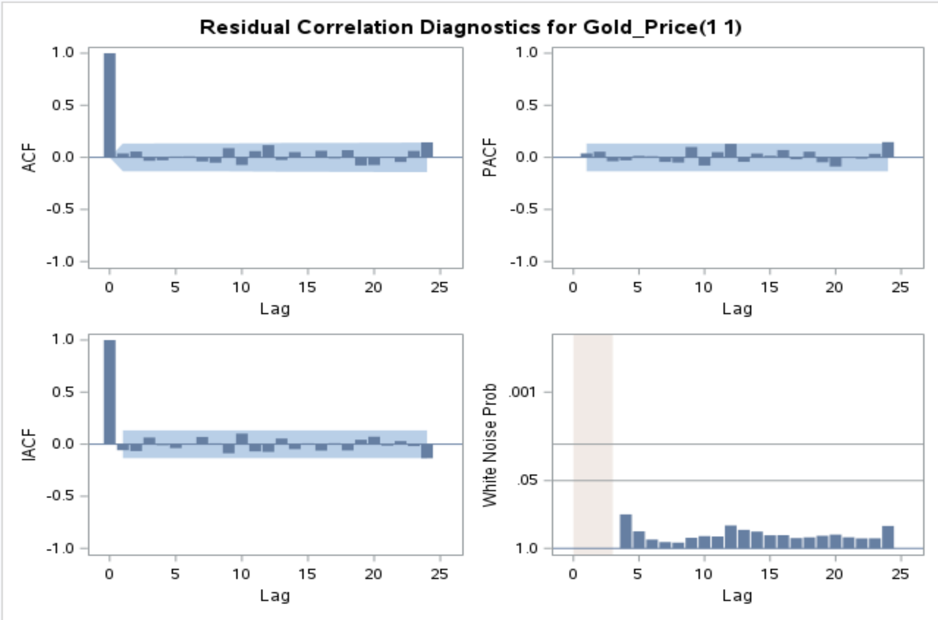

Figure 2. Residual Correlation Diagnostics for gold prices

The normal probability plot and Q-Q plot in Figure 3 indicate that the residuals tend to be normal. According to all previous results, the model has captured all relevant information in the data.

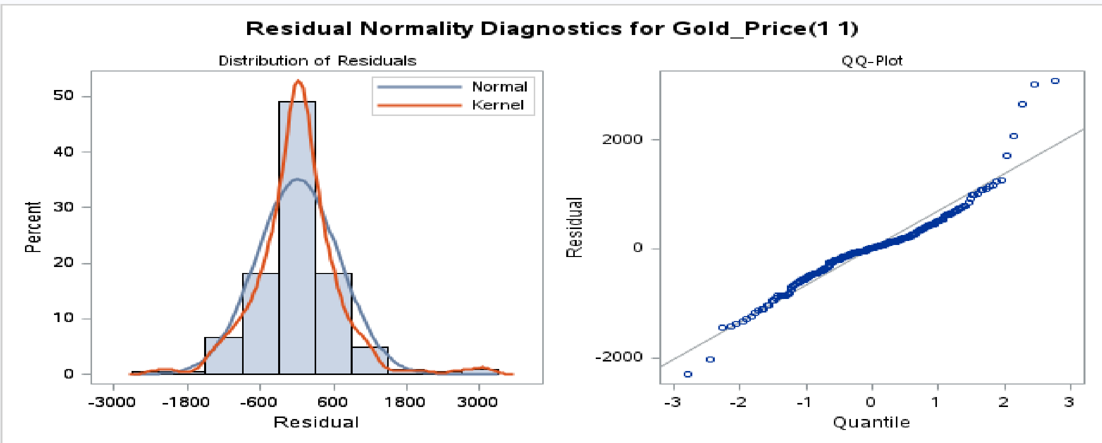

Figure 3. Residual Normality Diagnostics for gold prices

5.2. Simple Linear Regression model

In this paper, a Simple Linear Regression model has been built between gold prices and its first lag. Lag refers to the observation from a previous period. In this data, gold prices have been shifted one time period to create a new variable for lagged values. Based on the value of Pearson Correlation of 0.99791 between gold prices and first lag, there is a strong positive linear association between the gold prices and their first lag values.

Simple Linear Regression is a statistical method used to explain the connection between lag 1 gold prices as the predictor and gold prices as the response variable. It precisely explains the linear relationship between them. The Analysis of Variance (ANOVA) is used to determine how the overall variation in gold prices can be divided in order to test the hypothesis that the slope for lag 1 is equal to 0. The ANOVA analysis reveals a p-value that is extremely significant. So, the conclusion is that the Simple Linear Regression model fits the data better than the baseline model and the slope for date is significantly different from zero. Based on the value of R-square (Coefficient of determination), 99.58% of the variability in gold price can be explained by lag 1. In the Parameter Estimate, the p-value associated with the intercept is greater than alpha (0.05), and this indicates that there is not enough evidence to reject the null hypothesis that the intercept is equal to zero. The regression equation that can be used to forecast future prices is as follows:

Gold price= 1.00149* gold price lag 1

In order to ensure that the results of the Simple Linear Regression model are reliable, it is important to achieve the fulfilment of four different assumptions. The plot that can be seen in the middle panel of Figure 4 indicates that there is a linear connection between the average price of gold and the price of gold during the first lag. This is the conclusion that can be drawn from the data. On the basis of the Quantile-Residual plot that is located in the panel on the left-middle of Figure 4, it is possible to draw the conclusion that the residuals adhere to a normal distribution with a mean value of 1. A constant variance for residuals is depicted in the plot that can be seen in the top-left panel. This figure takes into account all of the different gold price lag levels. In addition to this, it highlights the fact that the residuals are independent and uncorrelated with one another. In conclusion, the findings of the Simple Linear Regression are reliable, which implies that the model well fits the data. This is stated in the conclusion. This is due to the fact that each and every one of the earlier assumptions has been fulfilled.

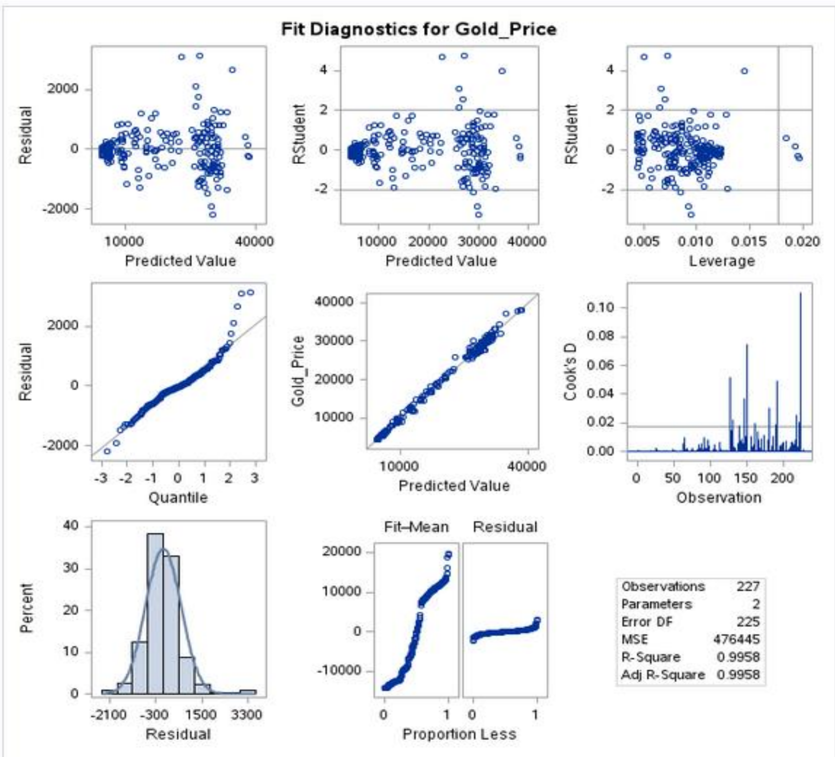

Figure 4. Fit Diagnostics for gold prices

5.3. LSTM and GRU models

There are two (2) levels of LSTM that make up the LSTM paradigm. The first layer is comprised of sixteen units, while the second layer offers twenty units. For the purpose of determining whether or not a neuron ought to be engaged and contribute to the total output of the model, the LeakyRelu activation function has been utilized in both layers. There are three layers that make up GRU models, each of which has 16, 32, and 64 units each. The activation function known as Relu has been utilized in each and every layer. Both models have been compiled with the help of the Adaptive Moment Estimation (Adam) optimizer and the Mean Square Error (MSE) algorithm. The ADAM algorithm is an optimisation tool that is used to alter the weight and bias of each backpropagation pass that occurs during training. The mean squared error (MSE) is a loss function that is used to calculate the error that exists between the anticipated values and the actual values.

5.4. Models' performance comparison

The dataset was split into two subsets in order to evaluate the performance of the metrics that were utilized, namely RMSE and MAPE. The training set consisted of 70% of the data for the building of models, while the test set consisted of 30% of the data for evaluating the predictive accuracy of the model for ARIMA and basic linear regression procedures. The test set for LSTM and GRU consisted of twenty percent, while the validation set consisted of ten percent. The remaining seventy percent of the set was used for training purposes.

The performance of LSTM and GRU models on both training and validation data is consistent, which indicates that they are neither over-fitting nor under-fitting. The results are presented in Table 3. As the results explain, the Simple Linear Regression model with RMSE and MAPE values 834.67 and 2.22%, respectively, outperformed the ARIMA model with RMSE value of 7121.1, and MAPE value of 22.9%. This proves that a simple linear relationship between gold prices and their previous values (lags) can effectively capture the trend in gold prices. Among the RNNs models, the LSTM model, with RMSE value of 1160.5, performed better than the GRU model with RMSE value of 1214. On the other hand, GRU outperformed slightly better than LSTM according to MAPE values. GRU value of MAPE is 2.83%, and LSTM value is 2.96%.

Table 3. Performance metrics results

	Metrics	
Algorithms	**RMSE**	**MAPE**
ARIMA	7121.1	22.9%
Simple Linear Regression	834.67	2.22%
LSTM	1160.5	2.96%
GRU	1214.8	2.83%

According to the comparison in Table 4, Simple Linear Regression model outperformed same type of model in Tripathy, (2017) based on both R-square and MAPE values. Both of models applied on monthly gold prices data. LSTM model showed higher performance than the model in Yang, (2019). based on MAPE measure. Moreover, ARIMA model is better, in term of AIC, compared to the model in Thakur, (2018).

Table 4. Results of this study outperformed some previous studies

<table>
<tr><th>Model Type</th><th>Ref.</th><th>Measure</th><th>Value</th></tr>
<tr><td rowspan="4">Simple Linear Regression</td><td rowspan="2">This study</td><td>R-square</td><td>99.58%</td></tr>
<tr><td>MAPE</td><td>2.22%</td></tr>
<tr><td rowspan="2">Tripathy, (2017)</td><td>R-square</td><td>78%</td></tr>
<tr><td>MAPE</td><td>8.40%</td></tr>
<tr><td rowspan="2">ARIMA</td><td>This study</td><td rowspan="2">AIC</td><td>3603.5</td></tr>
<tr><td>Yang, (2019)</td><td>9947.061</td></tr>
<tr><td rowspan="2">LSTM</td><td>This study</td><td rowspan="2">MAPE</td><td>2.96%</td></tr>
<tr><td>Hansun & Alethea, (2021)</td><td>17.66144</td></tr>
</table>

In general, by comparing the results of this study in Table 4, and the results of previous studies in Table 4, the results of this study are not considered as the best for gold price forecasting. Even though, this study demonstrates the superior predictive power of Simple Linear Regression compared to other methods, with an R-square value of 99.58% and a low MAPE value of 2.22%. Also, LSTM and GRU exhibited promising performance with MAPE values below 3%, although, the methodology employed in this study was limited to a univariate time series approach that relied solely on gold prices.

The performance of ARIMA is significantly worse than the other models, as evidenced by both the RMSE and MAPE metrics. This implies that ARIMA may be encountering difficulties in dealing with the intrinsic patterns or unpredictability of the data. ARIMA models excel at capturing linear dependencies in time series data. However, if the data exhibits nonlinear patterns, seasonality, or necessitates the management of more intricate connections, the effectiveness of ARIMA can noticeably decline. Simple Linear Regression demonstrates superior performance in terms of both Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). This suggests that the association between the predictor factors and the target variable could be effectively represented by a linear model. LSTM models are specifically engineered to process sequences and effectively capture complex relationships over lengthy periods of time in the given data. The findings indicate that LSTM outperforms ARIMA but has a little inferior performance compared to Simple Linear Regression. GRU, like LSTM, is specifically intended for processing sequential input and has the ability to grasp temporal dependencies. The performance of the Gated Recurrent Unit (GRU) is on par with that of the Long Short-Term Memory (LSTM), suggesting that they possess equal advantages and disadvantages. It is important to provide more attention to external factors and use more sophisticated modelling methods to enhance the accuracy of predicting.

6. Conclusion

This research was conducted with the intention of determining the degree of accuracy that various models possess in terms of forecasting gold prices in the Indian Rupee. It is well known that the price of gold is quite volatile, since it is capable of moving in both the upward and downward directions equally. The development of a trustworthy forecasting model has the potential to improve decision-making and reduce risks associated with gold investments. Within the scope of this investigation, the efficacy of four distinct models was evaluated and compared with regard to their capacity to forecast gold prices. It was determined that ARIMA, simple linear regression, and RNNs (LSTM and GRU) were among the models that were assessed. It was determined that the Simple Linear Regression model performed better than the ARIMA model based on the findings. For the purpose of further enhancing the predictive power of the models, it could be advantageous to take into consideration the possibility of including additional variables that have the ability to influence gold prices. These variables include interest rates as well as a variety of economic and geopolitical characteristics.

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