VOL. 19, NO. 4, FEBRUARY 2024 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

PREDICTION OF GOLD PRICE WITH COMPARISON OF FORECASTING METHODS

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ABSTRACT

Gold has emerged as an extra famous and very beneficial commodity in phrases of investment. Gold has been considered, as a country wide reserved commodity for many years, which leads to very integral for the economy of any country. Most people and traders believe that gold is a protected investment from uncertainty and political chaos. The rate of motion of gold helps the buyers from the centre of attention in their investments; they make use of the year by year information from Indian Gold Council. The analysis of the data was taken from 1964 to 2020. This paper's motto is to analyze and summarize different algorithms for predicting the rate of gold. The procedures utilized to fit the data were from the Time Series analysis Auto Regressive Integrated Moving Average (ARIMA) and Neural Network models; Multi-Layer Perception (MLP) and Extreme Learning Machine (ELM). The test data were utilized for the analysis, and then the outcome was exhibited with the help of error parameters. ELM is best as compared to ARIMA and MLP. The error measures are RMSE (1634.975) and MAPE (3.002). The error measurements have been represented in the tables for ARIMA and MLP. The best prediction of Gold price was given by the ELM, which is be efficient and accurate model.

Keywords: ARIMA, MLP, ELM, RMSE, MAPE, and gold.

Manuscript Received 21 December 2023; Revised 5 March 2024; Published 15 April 2024

INTRODUCTION

Among the available minerals in the earth's crusts, gold is the most valuable and popular choice for investment in the world. Despite making valued commodities, gold acts as a reserve in any country. A gold fund is an amount of gold held by any nation's central bank to guarantee pay or trade in the world market and increase the country's economy (Gavin Bridge, 2014). The price of gold is affected by different factors such as demand and supply, inflation rate, and political issues making the price unstable. The inflation rate is a sign of the economic stability of the country. The gold prices increase when the inflation rate increases and there is a low supply of gold. The dollar rate also influences the cost of gold because the dollar is the world's trading currency (Yu-Shan *et al,* 2013). Hence, the price of gold moved up and down and was very uncontrollable. Figure-1 shows the variation of the gold price for about 58 years, thus from 1964 to 2020. However, the gold price can be predicted (Brabenec T., *et al.*, 2020), making it possible to make future decisions. The variation of the gold price is time-series, which means changing the cost with time; therefore, forecasting the gold price has been challenging for a while until the application of machine learning models was introduced in economics. In this study, auto-regressive integrated moving average (ARIMA), multi-layer perceptron (MLP), and extreme learning machine (ELM) models have been deployed to determine the future price of gold.

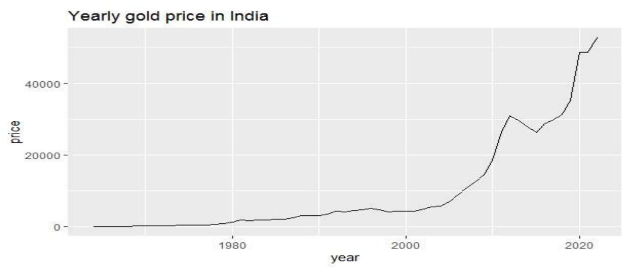

Figure-1. Exploring the gold price movement from 1964 to 2020.

In this study, ARIMA models, MLP, and ELM models have been deployed to determine the future price of gold. Arima is one of the most traditional models and widely used method. This model is compared with the scientific algorithms MLP, and ELM which are machine learning technologies. The study is divided into sections where in section 1. the Introduction to a theory about this article has been explained well as shown above. The remaining journal has been set as Section-2, which illustrates past similar works, Section-3, handles with methodology used and Dataset, Section-4, describes the results and analysis, a summary of results and advocacy have been given in section-5.

LITERATURE REVIEW

Forecasting analysis has become more interesting due to the huge increase in the availability of data which changes continuously with time. Researchers and Data Scientists are continuously working on extremely in business problems and natural problems to give the best results were shown in this challenge. The Arima method helps to predict the future gold price in India, based on the data from November 2003 to 2014 and concludes that the Arima model is performing well and is the best when forecasting in small intervals of time (Bandyopadhyay G, 2016). Arima can be used in the prediction of cattle products as in 2019; Joseph (Mgaya J. F., 2019) makes use of the Arima approach to predict cattle product consumption in Tanzania. In their research evaluation, their findings indicate that consumption of all farm animal products will make bigger, and on the pinnacle of that, they concluded that the demand for animal feed has to be anticipated soon. Hossain, Abdulla, and Zakiri compare the accuracy of forecasting jete manufacturing in Bangladesh. They were in contrast to the two mannequins Arima and ANN. The result of their paper indicates that ANN performed higher than the Arima mannequin (Md. Moyazzem Hossain. *et al.,* 2017). In the comparable manner of evaluating the models, Ayodel and others use New York Stock Exchange records to evaluate Arima and ANN, and the result of their find out about truly points out the ideal of ANN over the Arima Model (Adebiyi A., *et al*, 2014).

Generally, the previous research advocates that when the Arima mannequin is in contrast with the AI fashions such as deep getting to know and laptop mastering models, the Arima mannequin emerges as very vulnerable as explained extra this preceding work(Makala Dand Li Z., 2019) (Soy TemürA, *et al,* 2019) Weyden'sH., *et al,* 2019). With the boom of technology, lookups, and academics have engaged themselves in the usage of the higher way to analyses and discover answers the usage of the greater technological means. In prediction evaluation, some researchers have achieved some lookup on the overall performance of the SVM in forecasting. One of the places is a prediction of soccer results. (Igiri C.P, 2015) develop a mannequin to predict the soccer fit consequences in his findings and effects he has taken a look at that solely 53.3 prediction accuracy has been achieved from SVM. He concluded by suggesting that SVM is no longer appropriate and sufficient for the prediction of suit results. Again Minglei et.al (Shao M, *et al.*, 2020), evaluated the power consumption of resort buildings. The MSE cost of their result has the same opinion as much research that SVM is one of the first-class methods in prediction by way of having an MSE of 2.2% and R-square of 94%. (Akash *et al.,* 2016), use the information from the Perth Mint of Australia to predict gold rate the usage of SVM and ANFI with the aid of performing tolls mechanism of MAE, RMSE, and MAPE, it was once discovered that SVM carried out higher than ANFI. In addition to that (Isto FKuus, *et al*., 2014) explain greater about the utility of SVM in distinct components such as medical. The literature additionally advises about the significance of measuring the overall performance of forecasting with extraordinary methods. (Mehdiyev N. *et al.,* 2016) (Ouenniche J. *et al*, 2014) explained for special about the measurements and the necessity of them in forecasting. Also (Klimberg R K, *et al*, 2010) said that the right overall performance is a crucial issue to commercial enterprises and can have indispensable have an impact on an organization.

MATERIALS AND METHODS

Dataset

This investigation is aimed at the best method for forecasting the price of gold using machine learning methods. Data collected in this study research are the yearly gold price that can be collected from the Gold Council (Anon Gold hub). The rate from the Gold Council is indicated as per troy ounce. The dataset consists of the yearly prices from 1951 to 2020, thus it makes the total number of years of observation 70.

Next comes the cleaning of the data to make sure all the data is in the correct way and well arranged. Missed data is filled by the average of the past three years. After that, the splitting of the data was completed. In this step, the dataset is divided into training data and test data. Test data is used to train the model, and test data is used to verify how the model was trained. This study aims to use the ARIMA, MLP, and ELM to determine the forecast of gold prices, therefore knowledge of these models is required.

ARIMA: Time series forecasting has been using different methods to find the best forecasting method, especially in business and econometrics. One of the best ways is to apply an ARIMA model in forecasting. ARIMA stands for Autoregressive Composite Moving Average. The ARIMA model began a few years ago when statisticians and economists did not take into account the stationarity of the data; they have an impact on the prediction of results. George Box and Gwilym Jenkins presented prediction and control, where they explained how non-stationary data can be stationary.

ARIMA is one of the popular models for econometric and statistical analysis of time series data. This model is mainly and widely used when the dataset involves showing non-stationarity. This model is also known as the Box-Jenkins method. When seasonality is involved, the Arima pattern is expressed as ARIMA (p, d, q). When there is a seasonality, it is expressed as ARIMA (p,d,q)(PDQ)m. p is the autoregressive number, also known as the lag order, d is the number of non-seasonal differences, q is the number of moving averages, and m is the number of cycles per season 2 and 3. When (p, d, q) becomes zero, the ARIMA model becomes AR, I, or MA. For example, when the value of (p, 0, 0), ARIMA is equal to AR (p).

When making predictions with an Arima model, it is important to decide which ARIMA model to use. This means that the value of pdq should be determined and calculated. This model uses the fit () function when training the model. One thing to keep in mind is that time series should be stationary when calculated. Stationarity can be checked using different methods, but in this study follows:

ARIMA is the time series analysis model: Time series analysis projects deal with the data that scales according to the time and the goal of the projects to perform the forecasting for the future. The time series analysis also depends on the following factors:

a) Stationary (b) Seasonality (c) auto-correlation. Time series analysis can be implemented using different methods and technologies but choosing the efficient method can increase the accuracy rate of our forecasting. One of the best applications of time series analysis is "ARIMA" which stands for 'Auto Regressive Integrated Moving Average'. A few years back Statisticians analyzed time series trends can be forecasted without considering the non-stationary data and performed better as compared to other models George Box and Gwilym Jenkins have come up with an approach that converts non-stationary data into stationary and the traditional ARIMA model is deployed when data doesn't have any linear trend which means data is stationary.

Here instead of working on previous time series we design a new time series based on the data of past time series and our new series trend has constant mean, variance, and covariance. Mathematically it can be stated as: $z_t = a_{t+1}+a_t$ Where: z_t is a variable which we are trying to predict. a_{t+1}: The present trend data points of an instance. Arima mode is represented as ARIMA (p, d, q) and furtherer has three parameters p=Auto Regressive part, q=Moving Average part, d=integrated (difference between the two trends).

When seasonality comes into action then it is denoted as ARIMA (p, d, q) (PDQ)m. p is the number of numbers of autoregressive also known as lag order, d is the number of non-seasonality differences, q is the number of moving average times and m is the number of periods in each season 2 3. When two values of the (p, d, q) become zero, the ARIMA model becomes either AR, I, or MA. Example: when the value of is (p, 0, 0) then ARIMA becomes equal to AR (p) and the value of is (0, 0, q) then it becomes MA (q). The traditional Mathematical equation is: $z_t = \emptyset \cdot z_{t-1} + \theta \cdot \varepsilon_{t-1} + E_t$; z_t: our integrated bit. z_{t-1}: The autoregressive bit is managed by the autoregressive part. $\theta . \varepsilon_{t-1}$ The moving average bit. E_t= basic error. These are the predictions but the actual forecasting can be done mathematically referencing a variable a_k which is our future prediction in the given trends and we relate with, a_l: the last recorded data: The final summation of all the differences of previous trends and mathematically is given by:

$\sum_{i=1}^{k=l} z_i = z_{k-1} + a_l$ This is how ARIMA works and we should always be attentive while the data in which this technology is applied must be stationary and we can have better results for future and profits for the companies if they want to invest in a particular stock Augmented Dickey-Fuller test. The test has a Hypothesis that states: (i). Null Hypothesis H_0: unit root is present in a time series sample (nonstationary). (ii). Alternative Hypothesis H_1: There is No unit root in a time series sample (stationary). When the P-value is greater than the critical value (mostly 5%), the null hypothesis cannot be rejected. The Null hypothesis can be rejected when the P value is less than or equal to 0.05. As can be seen from Table-1, the P value is 0.099, which is much larger than the critical value for all significant levels. The most important value of ADF statistics is greater than the critical value. For this reason, this study fails to reject the null hypothesis (simply accept the null hypothesis) that the time series data has a unit root and that it is non-stationary. The need to make stillness there is crucial. Here we check whether the first differentiation is stationary or not. If it is not stationarity then it can be performed the second differentiation. The number of differentials is also called lag terms in Arima (p, d, q), and the number of differentials is d. After the first differentiation, it turns out that the P-value changes to 0.00, which means that the study rejects the null hypothesis and accepts the alternative hypothesis, which states that the data series have no unit root and that the data are stationary. Artificial Neural Networks: The term artificial neural network refers to a biological subfield of artificial intelligence modeled after the brain. Artificial Neural Networks is a computational network. Artificial neural networks also have neurons that are linked to each other in various layers of networks; these neurons are called nodes. ANN in the field of AI where attempts to mimic the networks of neurons that make up a human brain so that computers will have an option to understand things and make decisions in a human like manner. There are 1000 billion neurons in the human brain. Each neuron has an association point somewhere in the range of 1,000 to 100,000. The human brain is made up of incredibly amazing parallel processors.

ARCHITECTURE OF ARTIFICIAL NEURAL NETWORKS

Input layer and hidden layer: The input layer accepts different formats of input by programmers. A hidden layer is placed between input and output. Hidden layer features patterns. It is an intermediate layer between the input and output layers.

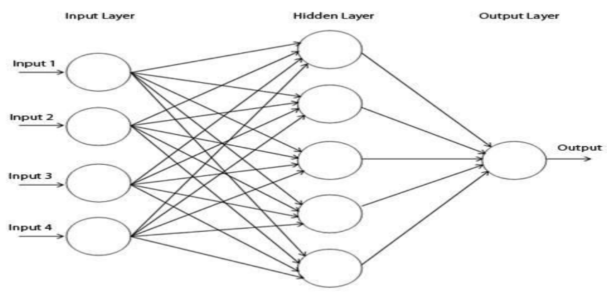

Figure-2. Architecture of artificial neural networks.

Output layer: Several series of transformations are used by the hidden layer. It results in output and using these layers. The artificial neural networks take input and compute the weighted sum of the inputs and include a bias, this computation is represented as bias. It is an additional parameter in the neural networks. Here it is used to adjust output along the weighted sum of input to neurons. In the form of a transformation function.

$\sum_{i=1}^{n} w_i + x_i + b$ It determines the total weighted sum passed as input data to activation functions to choose whether a node should fire or not. Enhanced Dickey Fuller test: This is the most important and the Box-Jenkins model uses generally three principles. Those are auto regression, difference, and moving averages which can help us to predict the data. These three principles are called p, d, and q, respectively. Each principle is used in the Box-Jenkins analysis and together they are shown as ARIMA (p, d, q) (Kamil R, *et al*, 2018) (Gordon Scott C. 2019). Package nnfor (package in R language) facilitates time series forecasting using multilayer perceptrons (MLPs) and extreme learning machines (ELMs). Currently, it does not support deep learning, but there are a few plans to expand it in this direction shortly. Presently, it relies on R's neural network package, which provides all the mechanisms for training MLPs. The training of the ELM is written in the nnfor package. Note that large networks tend to be very slow to train because neural networks cannot take advantage of GPU processing. nnfor differs from existing R neural network implementations in that it provides code to automatically design networks with reasonable predictive performance, but also provides in-depth control for experienced users. Autospec is designed with simplicity in mind. This increases the robustness of the generative network but also helps reduce training time.

Evaluation measurement metrics: Determining the best forecasting model is a crucial part because it indicates how best the forecasts are. Someone has to know if the forecast is good, then predictions are accurate. Usually, a good forecast is determined by comparing the predicted value with the true value. Different scholars have discussed different tools to determine the performance of predictions. This study uses RMSE, MAPE, and R-square to determine performance. RMSE means root mean square error is a standard deviation of forecast error. It measures the best fit of the regression line. This means that the RMSE shows how concentrated the data is around the line of best fit.

Root Mean Square Error = $\sqrt{\frac{\sum_{i=1}^{n}(O_i - A_i)}{n}}$

Where O_i = observed value; A_i = Actual value. MAPE is the mean absolute percentage error. This metric is one of the most commonly used metrics for comparing and measuring forecast performance. It measures performance accuracy by calculating the mean absolute percentage error minus the actual value divided by the actual value.

MAPE = $\frac{1}{n}\sum_{i=1}^{n}\left|\frac{O_i - A_i}{A_i}\right|$ where O_i = observed value and A_i = Actual value. R-squared is a statistical measure of how close the data is to be fitted regression line. It is also known as the coefficient of determination or the coefficient of multiple determination for multiple regression.

$R^2 = 1 - \frac{R_{res}}{R_{tot}}$

Where

R_{res} = sum of squares of residuals

R_{tot} = total sum of squares

RESULTS AND DISCUSSIONS

Table-1.

Summary	
Minimum	**63.25**
First quartile	648.75
Median	3755.50
Mean	8442.50
Third quartile	7950.00
Maximum	48651.00

The below graph plotted gold prices from 1964 to 2020 (yearly). On the x-axis years and y-axis took prices (in rupees) which it is clearly showed there is no constant mean and variances in different time intervals which leads to be data is not stationary.

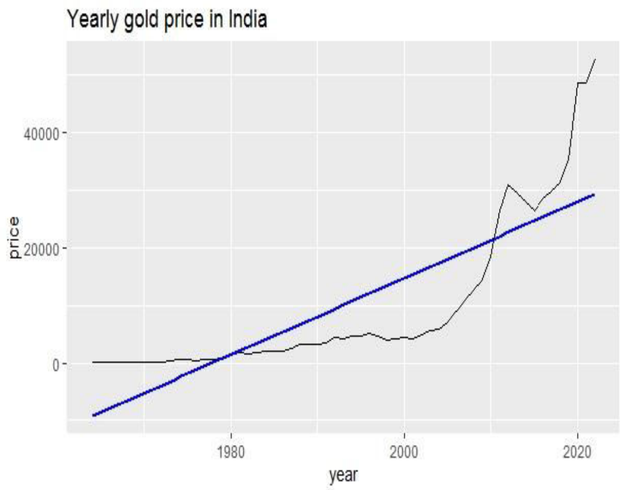

Figure-3. Explores graph of gold price yearly with mean straight line.

Arima results are discussed; one of the elements of the Arima model is to ensure that the time series data is stationary. To check the stationarity of data we used acf plot and Augmented Dickey-Fuller test to determine the stationarity state of the dataset.

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Table-2. Summary of adf test.

Lag	ADF	P-Value
Type: 1 No Drift and no Trend		
0	5.17	0.990
1	2.48	0.990
2	3.37	0.990
3	3.09	0.990
Type:2 with Drift and no Trend		
0	4.03	0.990
1	2.13	0.990
2	2.93	0.990
3	2.75	0.990
Type:3 No Drift and Trend		
0	1.772	0.990
1	0.862	0.990
2	1.503	0.990
3	1.450	0.990

The summary of the table above shows that the dataset is non-stationary, with a higher value of p. First we have to make sure that the data is stationary.

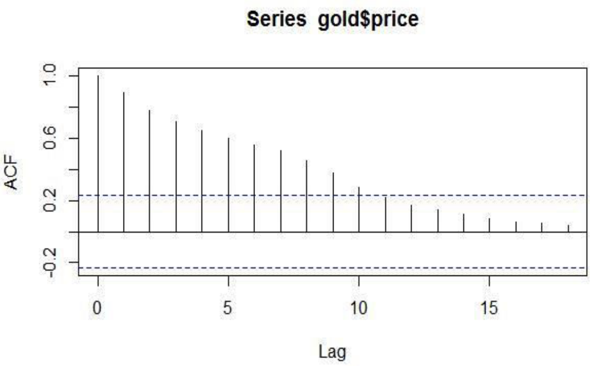

Figure-4. Acf graph.

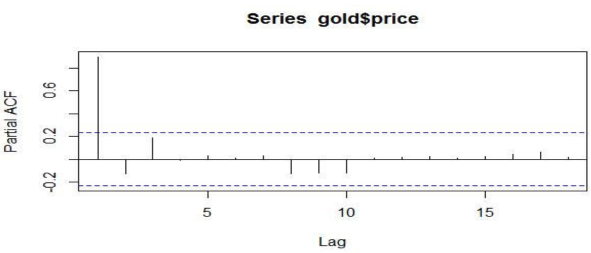

Figure-5. Pacf graph.

Here in Figure-3 ACF also shows the same graphically as like adf test, in which we observe that data values exceed the blue line, which also shows that time series data is stationary. PACF Figure-4 shows that there is no significant partial autocorrelation in data.

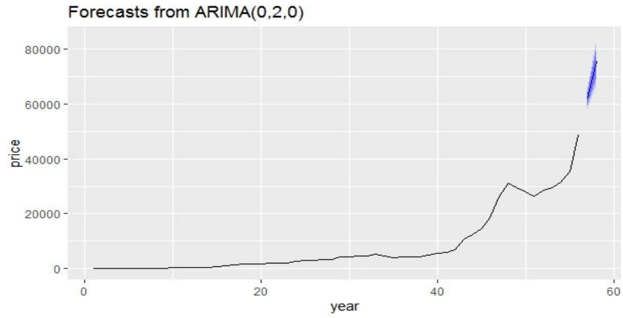

Figure-6. Showing the price prediction with the Arima model.

The above graph Figure-5 illustrates the prediction of gold prices near future, which was fitted with the (ARIMA) Auto-Regression-Integrated-Moving-Average model. In this p=0, refers number of past values that were being used to predict future values. d=2, refers amount of differencing for time series. q=0, refers number of time intervals taken to calculate the average price to predict future values. In this built Arima model; the mean absolute percentage error (MAPE) is 12.0985, root mean squared error (RMSE) is 1889.853, and R^2= 0.9746.

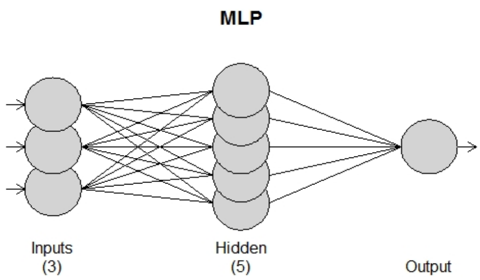

Figure-7. MLP Model.

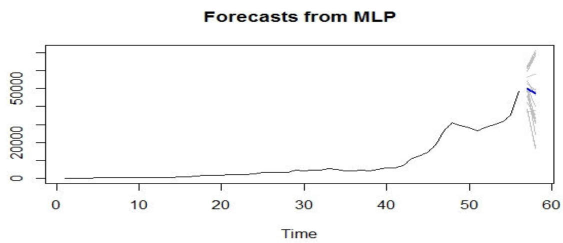

Figure-8. MLP model forecasting values.

This MLP model was built with three input nodes and five nodes in a hidden layer to build a neural network. The model takes three data values at a time and processing in a hidden layer gives a single output; this process repeats for all the data values to fit the model, for all the given data points. The below graph shows a fitted forecasted model using MLP to predict future data points (gold prices). In this, the built Arima model mean absolute percentage error (MAPE) is 9.9241, root means squared error (RMSE) is 529.0627, and R^2 = 0.9279.

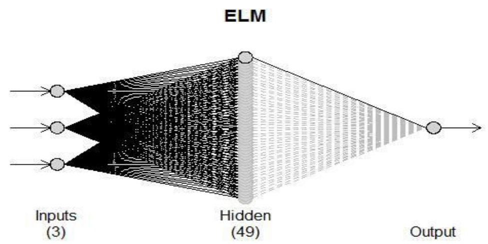

Figure-9. ELM Model.

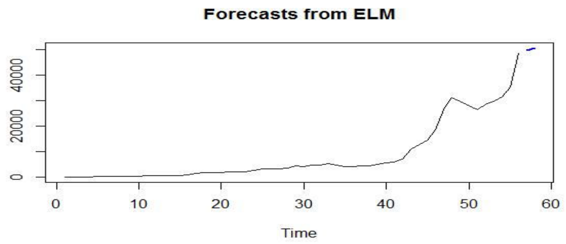

Figure-10. ELP forecasting values.

This ELM model was built with three input nodes and forty-nine nodes in a hidden layer to build a neural network. Model taking three data values at a time and processing in a hidden layer gives a single output and repeats this process for all data values to fit model for the all given data points. The above graphs show a fitted forecasted model using ELM, to predict future data points (gold prices). In this, the built Arima model mean absolute percentage error (MAPE) is 34.83866, root means squared error (RMSE) is 28.16502, and R^2= 0.9251.

Table-3. Summary of R^2 values of the models

Model	R^2
Arima(0,2,0)	0.9746
MLP	0.9685
ELM	0.9251

Table-4. Summary of ARIMA Model Error values.

ARIMA	ME	RMSE	MAE	MAPE
Training set	239.6868	1889.853	880.6892	12.0985
Testing set	18092.5	18700.7	18092.5	25.8735

Table-5. Summary of MLP Model Error values.

MLP	ME	RMSE	MAE	MAPE
Training set	1.8536	529.0627	323.8085	9.9241
Testing set	2014.527	4043.684	3506.146	7.3373

Table-6. Summary of ELM Model Error values.

ELM	ME	RMSE	MAE	MAPE
Training set	9.6317	2393.661	1415.621	28.1650
Testing set	627.8529	1634.975	1509.618	3.0029

CONCLUSIONS

Among these models, the best model was found to be the Extreme Learning Machine (ELM). This can help in the prediction of Gold prices. The model ELM has shown the best performance to forecast it. This can be widely used in finance, economics, and weather prediction. It also opens new room for scholars and academicians to discuss and suggest a better way to improve models by using Arima and MLP on testing sets with R^2= 0.9251. ELM provides a more prominent choice to be used in forecasting and prediction analysis. In this research, MLP and ELM results are almost showed similar by having above 90% of R^2.

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