International Journal of Advances in Engineering and Management (IJAEM)
Volume 3, Issue 6 June 2021, pp: 450-459 www.ijaem.net ISSN: 2395-5252

Forecasting Gold Prices in India using Time series and Machine Learning Algorithms

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Submitted: 25-05-2021 Revised: 01-06-2021 Accepted: 05-06-2021

ABSTRACT: It is the desire for the Share market investors in a country is to have access to reliable forecast of gold prices. This is achievable if an appropriate model with high predictive accuracy is used. The main object of this paper is to compare the Time series models with Machine learning algorithm.The ARIMA model is developed to forecast Indian Gold prices using daily data for the period 2016 to 2020 obtained from World Gold Council.We fitted the ARIMA (2,1,2) model to our data and we picked this model which exhibited the least AIC values. Random forest and XGB algorithmsare also used by taking two lagged variables as an independent variables of dependent variable.The forecasting performance of the models evaluated using mean absolute error, mean absolute percentage error and root mean squared errors. XGB model outperforms than that of the other two models for forecasting the Gold prices in India.

KEYWORDS: Gold Prices, Box-Jenkins Methodology, ARIMA.lag variables, Random forest model, XGB model

I. INTRODUCTION

People investing in gold have mainly two primary objectives, one being to mix your investment basket and hence diversify the risk and will help you reduce the overall volatility of your portfolio and next is a hedge against inflation as over a period of time, the return on gold investment is in line with the rate of inflation. Investing in gold have evolved over a period of time for traditional ways by buying jewelleries or by modern way as purchasing gold coins and bars (which is available in scheduled banks nowadays) or by investing in Gold Exchange traded fund (Gold ETF). Gold ETF is in financial instrument of mutual fund in nature which in turn invests in gold and these are listed in a stock index. Gold Fund of Funds and Equity based Gold Funds are other instrument where investor can choose to invest in Gold having some variation like Gold Fund of Funds is an investment made on behalf of the investor without holding a Demat account and Equity based Gold Funds are investment which are not made directly in Gold, but investing in the companies, which are related to the mining, extracting and marketing of the Gold. Importance of the yellow metal has changed over a period of time. In India few thousands of years ago, countless Kings & Emperor, the then rulers of land in different parts of the country having different monetary Manuscript received July 6, 2014; revised October 14, 2014. System, but only Gold was treated as common exchange commodity. India is known to demand of gold mainly for jewellery fabrication where it makes in the top list of imports of gold as the production of gold in India for mining activities is very limited, but in our country the demand for the yellow metal is seasonal and are high during wedding season, Post harvest season and festival season and demand are down during monsoon season. As of today the exchange (National Stock Exchange & Bombay Stock Exchange) has introduced different instrument linked with Gold investment to simplify to purchase of gold from exchange without forgoing with different charges associated with purchase of jewelleries which ultimately reduces the return of investors while investment in yellow metal, so it is important for investors to be well informed about fluctuation in the price so that he can take wise decision in investing in Gold.

A time series is as an ordered sequence of observations taken at equally spaced intervals. While most of the statistical concepts depend on the assumptions the first one the observations are independent and the time series analysis the observations are serially correlated. Also, statistical methods are generally used for making inferences about the population based on a sample. However, in time series analysis it is almost impossible to have more than one observation at a given time point. Time series analysis can be applied in a variety of areas such as engineering, agriculture, economics, medical studies and social studies. For example, in economics, daily closing stock prices, weekly interest rates for banks, quarterly sales of companies, yearly earnings of industries can be

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regarded as time series and can be analysed using time series models. The main objectives of a time series models are description, explanation, prediction modelling and control. The sources of variation in terms of patterns in the time series data are mostly classified into four main components: secular trend, seasonal variation, cyclical variation and irregular variation. We have Non parametric Methods like the Artificial Neural Networks and parametric Methods. Some of the models under parametric are: Extrapolation of trend curves, Exponential smoothing, The Holt-Winters forecasting procedure and Box Jenkins procedure.

II. REVIEW OF BOX AND JENKINS APPROACH

In statistics and econometric studies, and in particular in time series analysis, an autoregressive integrated moving average (ARIMA) model is a generalization of an autoregressive moving average(ARMA) model. The Box–Jenkins methodology applies ARIMA models to find the best fit of a time series to past values of this time series, in order to make accurate forecasts. These methods are also applied where data show evidence of non-stationarity, where an initial differencing step (corresponding to the "integrated" part of the model) can be applied to remove the non-stationarity.

Let$\{Z_t\}$ be the time series. Then $\{Z_t\}$ is stationary if E (Z_t) = μ and V (Z_t) =σ_Z^2 for all t. Otherwise it is non –stationary. Let Z_1 ,Z_2….Z_N be an observed sample. If trend line is parallel to x-axis and variability is uniform for allvalues of t in the sample time series graph, then the time series is stationary. Alternatively, if the ACF of sample diesout for higher lag is an indication for stationary. The Box – Jenkins Methodology is valid for only stationary time series data. If the data is non – stationary, we convert it into stationary by stabilizing variance using logarithmic transformation and stabilizing mean using successive differencing. The Auto Regressive Integrated Moving Average model for the time series is denoted by ARIMA(p, d, q) and is defined by $\varphi(B)\nabla^d Z_t = \theta(B)a_t$where $\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \cdots \varphi_P B^P$ is polynomial in B of order p and is known as Auto Regressive (AR) operator,$\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots \theta_q B^q$is a polynomial in B of order q and is known as Moving Average (MA), operator, ∇= 1− B , B is the Backward shift operator $B^k Z_t = Z_{t-k}$and d is the number of differences required to achieve stationarity. AR(p), MA(q) and ARMA(p, q) may be obtained as particular case of it with parameter values (p,0, 0), (0, 0, q) and (p, 0, q) respectively.

The Box-Jenkins method consists of four steps: Model Identification, Estimation of the parameters, diagnostic checking and finally forecasting the model.

A) Model Identification

The general form of ARIMA(p, d, q) is $\varphi(B)\nabla^d Z_t = \theta(B)a_t$

i. To assess the stationarity of the process $Z_t$and, if necessary, to difference $Z_t$as manytimes as is needed to produce stationarity, hopefully reducing the process under study to the mixed autoregressive--moving average process:$\varphi(B)d_t = \theta(B)a_t$

Where $d_t = \nabla^d Z_t$

ii. To identify the resulting autoregressive--moving average (ARMA) model for d_t.

Our principal tools for putting steps i and ii.into effect will be the sample autocorrelation function and the sample partial autocorrelation function. They are used not only to help guess the form of the model but also to obtain approximate estimates of the parameters. Such approximations are often useful at the estimation stage to provide starting values for iterative procedures employed at that stage

iii. Another approach to model selection involves the use of information criteria such as AIC proposed by Akaike (1974a) or the Bayesian information criteria of Schwarz (1978). In the implementation of this approach, a range of potential ARMA models are estimated by maximum likelihood methods, and for each model, a criterion such as AIC (normalized by sample size n), given by \

$$AIC_{p,q} = \frac{-2\ln(\text{maximized likelihood}) + 2r}{n}$$

In the information criteria approach, models that yield a minimum value for the criterion are to be preferred, and the AIC values are compared among various models as the basis for selection of the model.

B) Estimation of the parameters

The values of the parameters that maximize the likelihood function, or equivalently the log-likelihoodfunction, are called maximum likelihood (ML) estimates.Given the data **d**, the log-likelihood associated with the parameter values

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$(\varphi, \mathbf{P}, \sigma_a^2)$conditionalon the choice of ($\mathbf{d}*$, $\mathbf{a}*$), would then be$\mathbf{l}_*(\varphi, \mathbf{P}, \sigma_a^2) = \frac{-n}{2}\ln(\sigma_a^2) - \frac{s_*(\varphi, \mathbf{P})}{2\sigma_a^2}$

Where

$$s_{*(\varphi,\mathbf{P})} = \sum_{t=1}^{n} a_t^2(\varphi, \mathbf{P}|\mathbf{d}_*, \mathbf{a}_*, \mathbf{d})$$

In the above equations, a subscript asterisk is used on the likelihood and sum-of-squares functions to emphasize that they are conditional on the choice of the starting values.

C) Diagnostic checking

Ljung and Box (1978)

In addition to considering the $r_k(\hat{a})$'s individually, an indication is often needed of whether,say, the first 10--20 autocorrelations of the $\hat{at}$'s taken as a whole indicate inadequacy of the model. Suppose that we have the first Kautocorrelations2 $r_k(\hat{a})(k = 1, 2, \ldots, K)$ from any ARIMA(p, d, q) model, then it is possible to show (Box and Pierce, 1970) that if the fitted model is appropriate, However, Ljung and Box (1978) later showed that, for sample sizes common in practice, the chi-squared distribution may not provide an adequate approximation to the distribution of the statistic Qunder the null hypothesis, with the values of Qtending to be somewhat smaller than what is expected under the chi-squared distribution. Empirical evidence to support this was also presented by Davies et al. (1977). Ljung and Box (1978) proposed a modified form of the statistic,

$$\mathbf{Q} = \mathbf{n}(\mathbf{n}+\mathbf{2}) \sum_{k=1}^{K} (n-k)^{-1} r_k^2(\hat{a})$$

such that the modified statistic has, approximately, the mean $E[\widehat{Q}] \approx K - p - q$of the $\chi 2(K - p - q)$ distribution

D) Forecasting

The future values are forecasted using minimum mean squared error forecasting method.

III. REVIEW ON ENSEMBLE LEARNING

Ensemble method is a machine learning technique that combines several base models in order to produce one optimal predictive model. In general, according to Allende and Valle, the advantages of combining models for time series forecasting can be credited to three facts, namely:

(i) It increases overall forecast accuracy to a large extent by using appropriate aggregation techniques,

(ii) There is often a great uncertainty about the optimal forecast model and, in such situations, combination strategies are the most appropriate alternatives, and

(iii) The combination of multiple forecasts can efficiently reduce errors

Types of Ensemble methods

a) Bagging

b) Boosting

Bagging- or bootstrap aggregating, is a classical technique for the creation of an ensemble proposed by Breiman. It was initially proposed for use in problems of classification. However, it can be used in problems that aim to perform data regression.

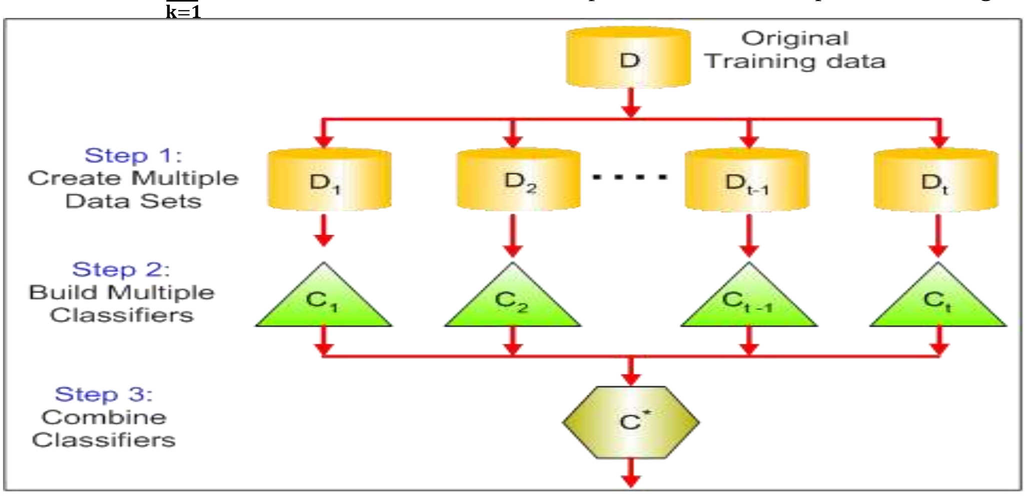

Figure 1: Work flow of Random Forest Algorithm

It is characterized by the creation of multiple samples, with refitting by means of the bootstrap technique, from the same set of data, so that it is possible to build multiple distinct trees for the same predictor and use them to generate an aggregate prediction. The final prediction from this process can be obtained by voting or average, for classification and regression problems respectively. This allows the generation of multiple samples for

the same set. One of the most popular technique under the bagging is Random forest.
Hyper Parameter Tuning was implemented in Random forest model by the following parameters:

- n_estimators = number of trees in the forest
- max_features = max number of features considered for splitting a node
- max_depth = max number of levels in each decision tree
- min_samples_split = min number of data points placed in a node before the node is split
- min_samples_leaf = min number of data points allowed in a leaf node
- bootstrap = method for sampling data points (with or without replacement)

Boosting-Boosting is an ensemble learning technique that uses a set of Machine Learning algorithms to convert weak learner to strong learners in order to increase the accuracy of the model.Boosting is a technique used to solve problems of classification and regression, which combines a set of models (decision trees), whoseindividual performance can be considered weak, whereas when the individual predictions are aggregated, a model of high accuracy is obtained.The central focus of this approach is bias reduction,that is, improving the suitability of the model to data. Several machine learning models have been proposed in this idea, using decision trees with individual learners, but we highlight the XGB model

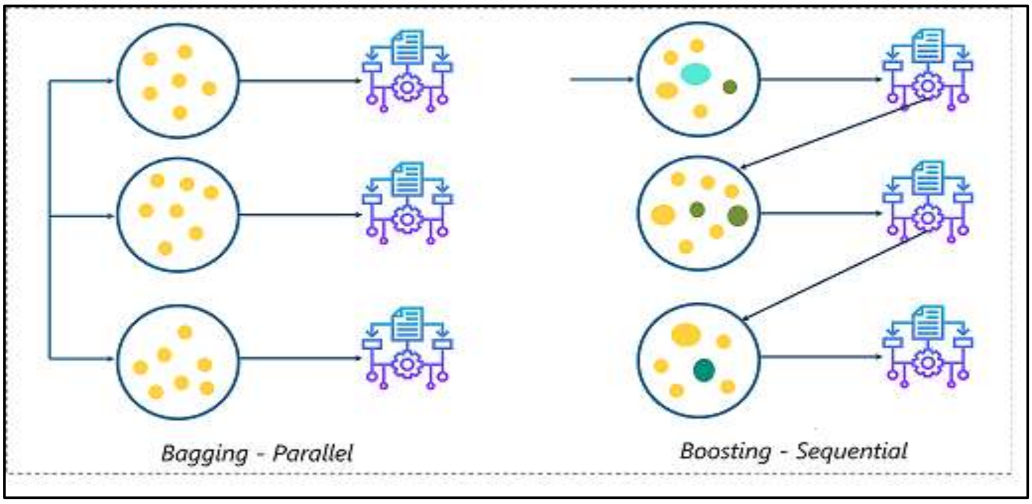

Figure 2: Work flow of Bagging and Boosting

Hyper Parameter Tuning was implemented in XGB model by the following parameters:

- **Max_depth** -The maximum depth of a tree
- **Min_child_weight-** Defines the minimum sum of weights of all observations required in a child.
- **Subsample-** Denotes the fraction of observations to be randomly samples for each tree.
- **Colsample_bytree-** Denotes the fraction of columns to be randomly samples for each tree.
- **Lambda-** L2 regularization term on weights (analogous to Ridge regression.
- **Alpha** -L1 regularization term on weight (analogous to Lasso regression)
- **Gamma** -A node is split only when the resulting split gives a positive reduction in the loss function. Gamma specifies the minimum loss reduction required to make a split.
- **Eta**-learning rate
- **Objective-** This defines the loss function to be minimized
- Eval_metric -The metric to be used for validation data.

Measures:
If Z_t is the actual price for period t and $\hat{Z}_t$ is the forecast, then the error is defined as $e = Z_t - \hat{Z}_t$. The following measures may be considered

Mean Absolute Error (MAE) $=\frac{1}{n}\sum_{t=1}^{n}|e_t|$

Root Mean Square Error (RMSE) $=\sqrt{\frac{1}{n}\sum_{t=1}^{n} e_t^2}$

Mean Absolute Percent Error (MAPE)$=\frac{1}{n}\sum_{t=1}^{n}\frac{|e_t|}{z_t}\times 100$

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IV. DATA AND METHODOLOGY

This study is based on secondary data collected from World Gold Council of gold prices () in Rupees per gram, daily frequency ranging from January 2016 to December 2020 consisting a total of 1304 observations. The data is split into train (98%) and test (2%). We built the model on train dataset and predictions on test dataset.

Table 1: Average Daily Gold Prices (Rs/Gram)

Average Daily Gold Prices (Rs/gram) in India				
Mon	Tue	Wed	Thu	Fri
2755.606	2756.874	2755.702	2756.907	2755.783

V. ARIMA MODEL

Model Identification

The first step in developing a Box–Jenkins model is to check if the time series is stationary.

Detecting Stationarity

Stationary can be determined from a run sequence plot. The run sequence plot should show constant mean and variance. It can also be detected from an autocorrelation plot. Specifically, non-stationary is often indicated by an autocorrelation plot with very slow decay in the lags.

Testing Stationary of Time Series

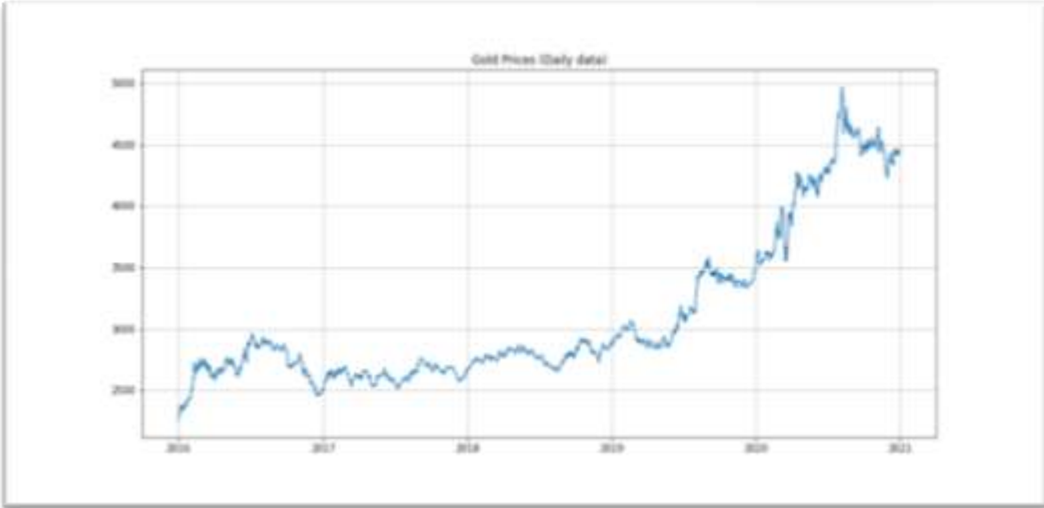

Figure 3: Time series plot of daily Gold Prices in India

Figure (3) indicates that the time series is not a stationary series. The plot showsconsistent patterns of short-term changes for data. This series varies randomly over time and there is general trend in the time series data.

The stationary condition can also be determined by the testcalled Augmented Dickey Fuller (ADF) unit root test. The hypothesis of the test are:

The null Hypothesis H_0: Xt is non – Stationary and
Alternative hypothesis H_1: Xt is Stationary p-value: 0.974
The p-value of the Augmented Dickey-Fuller (ADF) test equals0.996 and it is larger than the value of alpha= 0.05. This result indicates that the time series of daily Gold Prices in India is not stationary.

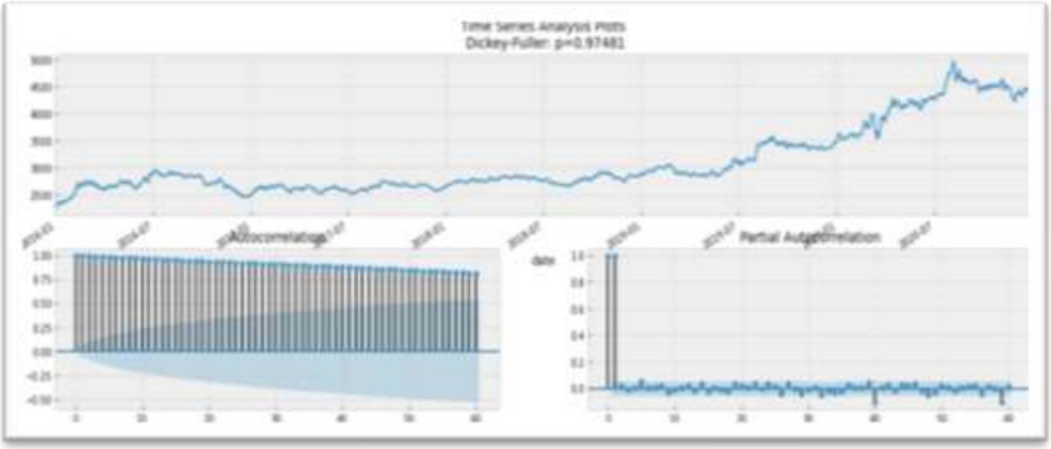

Figure 4: ACF and PACF for daily Gold Prices in India

All the above plots and results confirm that the original time series data is non stationary, and need to apply some transformations to convert it into the stationary series

Non stationarity in mean is corrected through appropriate differencing of the data. In this case, non seasonal difference of order 1 (i.e. d=1) is sufficient to achieve stationary in mean and variance. The newly constructed variable .$W_t = \nabla^1 \hat{z}_t$ can now be examined for stationary.

Figure 5 displays the time series plot of the data after first differencing the series and indicates that the time series is a stationary series. To make sure of that, we conduct the unit roots test (Augmented Dickey-Fuller) for the transformed series Zt .

The p-value of the ADF test equals 0.00 which is less than the value of alpha=0.05 and this indicates that the non-stationary hypotheses of the differenced daily Gold Prices data is rejected and this demonstrates the success of difference transformation for the time series data of daily Gold Prices data. Thus, the series became stationary.

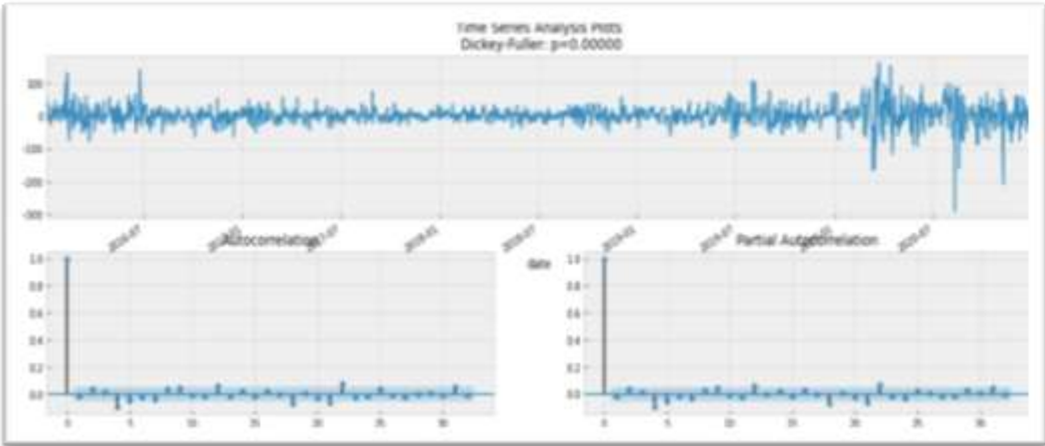

Figure 5: Time series plot,ACF and PACF of the first differences of daily Gold Prices in Indiaof the first differences of Daily Gold Prices in India.

Model Identification

This section shows how we determine the order of the ARIMA model and identify the model specifications. We computed all relevant criteria by trial and error method to select the best ARIMA model for the data. The Auto correlation function (ACF) and Partial Auto correlation Function (PACF) are used to determine the p and q values.

The AR(P) model is taken from the PACF plot and MA(q) model is drawn from the PACF.

From figure (5), the ACF starts from p1 value, this means that the series may be Auto Regressive (AR) and as we can observe the ACF cuts off after lag (4).On the same lines, it can be seen that the PACF of the stationary series cuts off after time lag (4).

The following tentative models have been examined and estimated as shown in table (2) below. The best ARIMA model is chosen through the AIC criteria if it shows the lowest values of these criteria.

Table (2): Tentative ARIMA Models Criteria for the daily Gold Prices in India.

S.No	Parameters	AIC	S.No	Parameters	AIC	S.No	Parameters	AIC
1	(2, 1, 2)	12,359.2	6	(2, 2, 1)	12,370.9	11	(4, 2, 2)	12,374.3
2	(4, 2, 1)	12,361.7	7	(1, 2, 1)	12,371.2	12	(1, 1, 2)	12,374.8
3	(4, 1, 1)	12,364.5	8	(3, 2, 2)	12,372.5	13	(2, 2, 2)	12,374.9
4	(4, 1, 2)	12,366.4	9	(3, 2, 1)	12,372.8	14	(3, 1, 1)	12,375.0
5	(3, 1, 2)	12,368.1	10	(1, 2, 2)	12,373.0	15	(2, 1, 1)	12,375.4

It is shown in table (2) that the ARIMA (2, 1, 2)is significant with respect to parameters as well as adequacy of the model. This means that the ARIMA(2, 1, 2)model is the best among all the other models.

Parameters Estimation:

Dep. Variable:	**Price**
Model:	ARIMA (2, 1, 2)
Sample:	01-01-2016 - 24-11-2021
No. Observations:	1277
AIC	12359.2
BIC	12384.9
HQIC	12368.9

Table: 3 Model Parameters of the ARIMA (2, 1, 2) Model

	coef	std err	z	P>|z|	[0.025	0.975]
ar.L1	-0.5181	0.015	-33.997	0	-0.548	-0.488
ar.L2	-0.9352	0.019	-49.252	0	-0.972	-0.898
ma.L1	0.4994	0.012	41.209	0	0.476	0.523
ma.L2	0.9742	0.013	72.402	0	0.948	1.001
sigma2	935.9803	16.118	58.069	0	904.389	967.572

So the fitted model for the daily gold price in India is

$$(1 + 0.52\mathrm{B} + 0.93\mathrm{B}^2)\, y_t = (1 - 0.50\mathrm{B} - 0.97\,\mathrm{B}^2) e_t$$

Diagnostic Tests:

Diagnostic checking is done through examining the autocorrelations and partial auto correlations of the residuals of various orders.

Analysis of residuals

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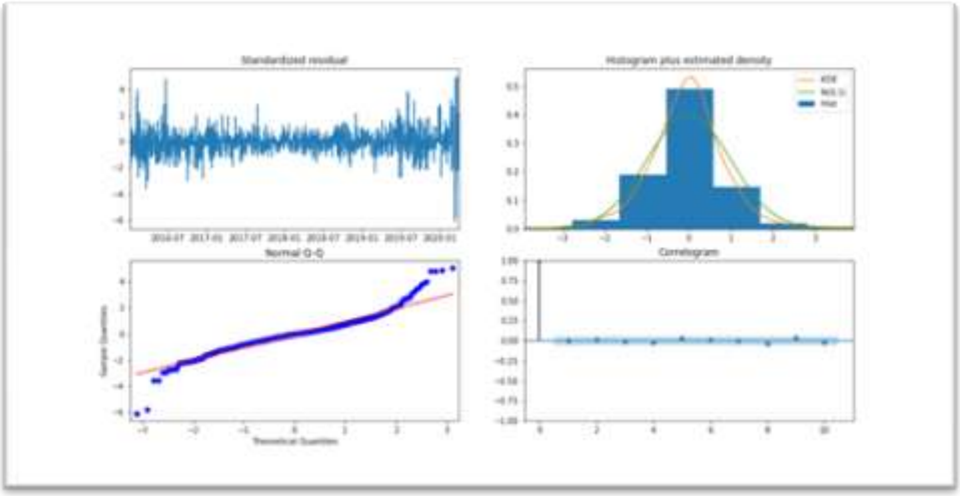

Figure (6): Residual Chart

Figure (6) show the estimated autocorrelation function for the residuals of theARIMA (2, 1, $2)_4$model for the time series of daily Gold prices. The standardized residual plot shows that the residual errors seem to fluctuate around a mean of zero and have a uniform variance. The histogram shows that the density plot suggest normal distribution with mean zero. The Normal Q-Q plot shows that all the dots should fall perfectly in line with the red line. Any significant deviations would imply the distribution is skewed. The Correlogram or ACF plot shows the residual errors are not auto correlated. Also we test the adequacy of the model by using Ljung-Box Statistic.

For this purpose, the various autocorrelations of residuals for 25 lags are computed and the same along with their significance which is tested by Box-Ljung Q- test statistic. Let the hypothesis on the model is
H0: The selected model is adequate.
H1: The selected model is inadequate.

Table (4): Ljung-Box Test Statistic

Ljung-Box (Q):	0.06		Jarque-Bera (JB):	7091.2
Prob(Q):	0.81		Prob(JB):	0
Heteroskedasticity (H):	3.21		Skew:	-0.67
Prob(H) (two-sided):	0.00		Kurtosis:	14.47

Figure (6) and Table (4), show that none of these autocorrelations is significantly different from zero at 5% level and Since the probability corresponding to Box-LjungQ-statistic is greater than 0.05, therefore, we accept Ho and we may conclude that the selected ARIMA model is an adequate model for the giventime series on daily gold prices in India.

VI. RANDOM FOREST

In this Section, we develop a Random Forest model for forecasting of daily gold prices (gms) in India. Python software is used to build a Random Forest model for forecasting of daily gold prices (gms) in India
The best parameters using Hyper Parameter Tuning on train dataset is:

RandomForestRegressor(max_depth=5, max_features=1, min_samples_leaf=9,min_samples_split=0.1, n_estimators=31, bootstrap=True,random_state=1)

VII. XGB MODEL

In this Section, we develop a XGB model for forecasting of daily gold prices (gms) in India. Python software is used to build a XGB model for forecasting of daily gold prices (gms) in India
The best parameters using Hyper Parameter Tuning on train dataset is:

XGBRegressor('max_depth': 3, 'min_child_weight': 2,'colsample_bytree': 0.5,'subsample': 0.77,'gamma': 0.0, 'learning_rate': 0.3, 'reg_alpha':

1e-05, 'reg_lambda': 0.1,'n_estimators': 150,'objective': 'reg:linear',random_state=1)

VIII. CONCLUSIONS

1. The statistical tests show that the time series of the daily gold prices in India is not stable. To achieve the conditions of the stability in the series, firstly, the trend wasremoved using the differences of the first lag.
2. The best and most efficient model ARIMA (2, 1, 2)among the possiblemodels was chosen using the balancing standards (the smallest value of each:AIC as well as the adequacy of the model using L-jungBox test).
3. The following tables presents the error measures for test data and the forecasts of the gold price (in gm) using the three models. We computed the forecasts for the given data using three models and computed the mean absolute error (MAE), root mean squared error (RMSE), mean absolute percentage error (MAPE) and are presented in the following table.

Table 5: Comparison of ARIMA, Random forest and XGB models

Model	MAE	RMSE	MAPE
ARIMA	97.33	70.10	2.20
Random forest	55.72	73.45	1.29
XGB	46.20	56.68	1.05

From the above table it is clear that, XGB model has very less error comparing to errors of the other models. Hence, the XGB model is suitable for the forecasting of gold prices. Forecasts for test data using XGB model presented in the following table (6).

Table 6. Gold price forecasts using XGB model for the test dataset

Date	**Actual Price**	**Predicted Price**	**Date**	**Actual Price**	**Predicted Price**	**Date**	**Actual Price**	**Predicted Price**
25-11-2020	4286.8	4341.5	**08-12-2020**	4434.9	4436.4	**21-12-2020**	4465.3	4438.9
26-11-2020	4298.6	4288.9	**09-12-2020**	4360.8	4470.3	**22-12-2020**	4416.7	4445.2
27-11-2020	4249.6	4292.8	**10-12-2020**	4352.9	4455.3	**23-12-2020**	4446.3	4512.9
30-11-2020	4230.0	4268.0	**11-12-2020**	4362.6	4403.9	**24-12-2020**	4437.4	4475.7
01-12-2020	4289.8	4261.8	**14-12-2020**	4327.8	4372.5	**25-12-2020**	4411.9	4400.1
02-12-2020	4342.1	4238.9	**15-12-2020**	4383.6	4403.9	**28-12-2020**	4428.8	4484.0
03-12-2020	4372.4	4292.8	**16-12-2020**	4414.2	4300.2	**29-12-2020**	4431.8	4470.3
04-12-2020	4362.2	4372.5	**17-12-2020**	4458.8	4374.0	**30-12-2020**	4456.3	4448.4
07-12-2020	4421.0	4373.3	**18-12-2020**	4450.0	4485.2	**31-12-2020**	4460.0	4453.7

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