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

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Abstract:The primary object of this paper is to compare the traditional time series models with deep 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 which exhibited the least AIC values. In the meanwhile, MLP, CNN and LSTM models are also examined to forecast the gold prices in India. Mean absolute error, mean absolute percentage error and root mean squared errors used to evaluate the forecasting performance of the models. Hence, LSTM model superior than that of the other three models for forecasting the gold prices in India.

Keywords: Gold Prices, Box-Jenkins Methodology, ARIMA,Lag Variables, MLP, CNN and LSTMModels

I. INTRODUCTION

Gold is a precious metal and it is completely different from other assets and metals. It is highly liquid and sensitive to price changes (Ranson and Wainwright, 2005). A majority of gold is bought as jewelry items. In the gold consumption, India and China together account almost 60% of worldwide gold jewelry. Gold is consider as a traditional gift in many weddings and often given away on the occasion offestivals, such as Diwali, Akshaya Tritiya and Dantheras.Gold plays a unique role as a store of value and hedge risks (Taylor, 1998; Hammoudeh et al., 2010). People investing in gold have mainly two primary objectives, one being hedge against inflation as over a period of time (Baur and McDermott (2010) and Baur and Lucey (2010) and next is to mix your investment basket and hence diversify the risk and will help you reduce the overall volatility of your portfolio. Typically the return on gold investment is almost in line with the inflation rate. In modern days, people has to choose different ways to invest the gold by buying jewelleries which is safer way or by purchasing goldcoins and bars which is available in public sector 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.

Time series can be defined as a sequence of data points which is ordered in sequence and collected at regular time intervals. Time series approach can be used on any data which is changes over time. Time series are used in statistics, weather forecasting, sales forecasting, stock market predictions etc. In decisions, that involve factor of uncertainty of the future, time series models found one of the most effective methods of forecasting. The classical time series analysis procedure decomposes the time series data into four components: Trend, Seasonality, Cyclic and residual component.

There are a wide range of techniques to forecast the gold prices. There are classic econometric and statistical techniques like the exponential smoothing method (ESM), autoregressive moving averages(ARMA), auto regressive integrated moving averages (ARIMA) etc., Although these methods are useful to capture the linear relationship and they fail to capture the non-linear characteristics of gold prices. To tackle this problem, artificial intelligence (AI) models are implemented to forecast the gold prices. The common methods are Feedforward neural networks, Multilayer perceptron (MLP), Recurrent neural networks (RNN), Convolutional neural networks (CNN) and Long short term memory (LSTM).

II. MATERIALS AND MEHODS

The 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 train and test datasetsconsists of 1277 and 27 respectively. 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

A. Review of Box and Jenkins Approach

The Box–Jenkins methodology is one of the well known method in the field of time series. This method applies ARIMA models to find the best fit of a time series to past values of this time series, in order to make accurate future forecasts. These methods are also commonly used when the data is not-stationarity.

Let$\{Z_t\}$ be the time series. Then $\{Z_t\}$ is stationary if $E(Z_t) = \mu$ and $V(Z_t) = \sigma_z^2$ for all t. Otherwise it is non –stationary. Let Z_1 ,Z_2….Z_N be an observed sample. If there is no trend line and constant variance for allvalues of t in the time series plot, then the time series is said to be stationary. Alternatively, if the ACF of sample diesout slowly 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 mean using successive differencing and stabilizing variance using logarithmic transformation. 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, $\nabla = 1 - B$, B is the Backward shift operator $B^k Z_t = Z_{t-k}$ and d is the number of differences required to arrive stationarity timeseries. 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 four steps procedure forBox-Jenkins method: Identification of model, Parameter estimation, diagnostic checking and finally model forecast.

B. Review on Deep Learning Algorithms

In the study of ANN, the most popular algorithm is a feed-forward neural network (FFNN). It has only forward connections in between the neurons. ANNS are commonly used for time series forecasting. ANNs can model any form of unknown relationship in the data with few assumptions. ANNmodels trained on train dataset and it can generalise on unseen data. Traditional time series are capable of modelling only liner relationships where as ANNs are capable of modelling any form of relationship in the data, especially non-linear relationships (Hornik et al., 1989). The forecasting accuracies are also better than other traditional time series models.

Tang et al. (1991) compared ARIMAmodel with deep learning model for forecasting and results show that deep learning models are better than the ARIMA. Claveria and Torra (2014) studiedperformance of ANNs and traditional time series ARIMA and finally showed that ANNs are higher accuratethan ARIMA model to a tourism-demand forecasting problem. Zhang & Kline (2007) paper revealed that the accuracy of the model is depends on the input variables, best network structure and also training procedure.

Multilayer Perceptron (MLP)

A multilayer perceptron(MLP)is a class of feedforwad artificial neural network(ANN). MLP Neural Networks can be formed a relation between the input and output data and it can be modelled by neural networks (Bildirici et al., 2010).It is an extension of feed forward neural network. A multilayer perceptron neural network with two hidden layers is depicted in Fig. 1 which consists of three types of layers—the first one input layer and output layer these two connected with hidden layers. In MLP, the input nodes are connected to the output nodes with the help of hidden layers in between the two layers. The input will be changed under the effect of the hidden layers, which behave in nonlinear way and the results of the changes multiply the weights will be transferred to the output nodes.Unlike to a feed forward network in a MLP the data flows in the forward direction from input to output layer. The number of neurons are trained with the back propagation learning algorithm. The major use cases of MLP are forecasting, recognition, prediction, pattern classification, and approximation.
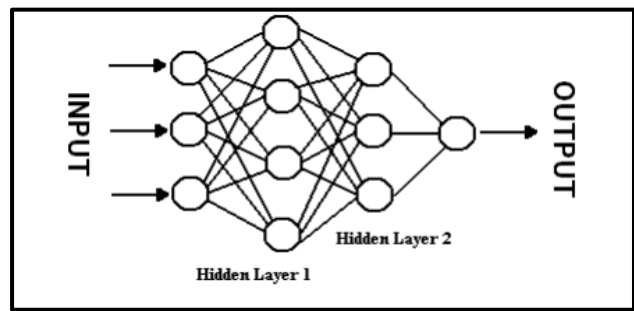

Figure 1. A simple schema of a three layer perceptron neural network

Fig. 1 representing a network structure of MLPwhere neural network has three inputs and two hidden layers with four and three nodes and one output node (3-4-3-1). A simple single layer perceptron is illustrated in the form of equation in Eq. (1).

$$o = f(\sum_{i=1}^{n} w_i \emptyset(x))(1)$$

In Eq. (1), the variable, x, is the input vector, $\emptyset$ is called the activation function and the output result of the MLP could be a number or a vector of zero numbers. The variable, w,is the weights and f is the output function. Log-sigmoid, ReLUand hyperbolic tangent are the different activation functions, which can be found in the neural networks literature. Activation function is the core of any node in the hidden layers of MLP changes the input of the node to the output. ReLUactivation function is used in this research which is presented in Eq. (2)

In deep learning models, the most commonly used activation function is Rectified Linear Unit. The function returns for any positive value x it returns that value back and 0 if it receives any negative input. It can be written as
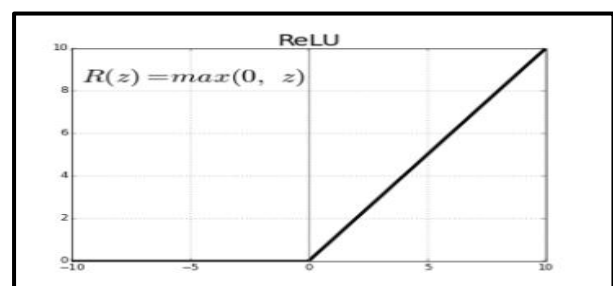$$f(x) = max(0, x)(2)$$

Figure 2. ReLU activation function

Long Short Term Memory (LSTM)

RNNs are a most powerful type of artificial neural network that can internally maintain memory of the input. In Recurent Neural networks(RNN) studies, one of the most common algorithm is LSTM.

The LSTM network is first developed by Hochreiter & Schmidhuber. Since RNN has maintain memory gate, this enables them particularly used for solving the time series problems.

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One of the drawback of RNNs isto suffer from a problem called vanishing gradient which leads to the model learning becoming too slow or stopping altogether. LSTM models are developed such that To avoid the vanishing gradient problem. LSTMs have longer memories and can learn from inputs that are separated from each other by long time lags. An LSTM has three gates: an input gate which determines whether or not to let the new input in, an output gate which decides what information to output and finally the import gate which is a forget gate which deletes information that is not useful. These three gates are analog gates based on the sigmoid function which works on the range 0 to 1which is shown in Fig. 3 below.LSTM component is a end-to-end feature (enclosed in green dash box) with a three-layer model (consisted of input layer, LSTM unit layer and output layer).
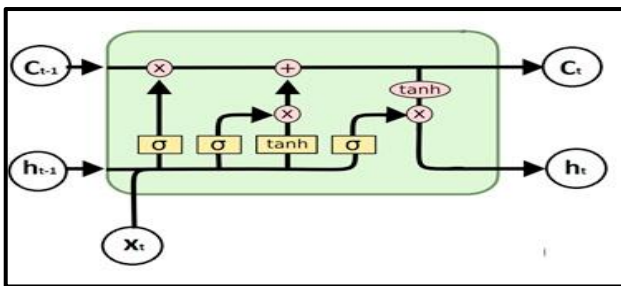

Figure 3. A simple LSTM Architect

Convolution Neural Networks (CNN)

In deep learning, a CNN is a class of Deep learning neural network, most commonly used for vision and image processing-based classification problems (object detection ,image classification, image segmentation, etc.). CNN are regularized versions of MLP. In MLP, each neuron in one layer connected with all then neurons of next layer. The "full connectivity" of these networks make them prone overfitting of the data. Regularization is one way to deal the overfitting in the data. CNN take a different approach towards regularization.
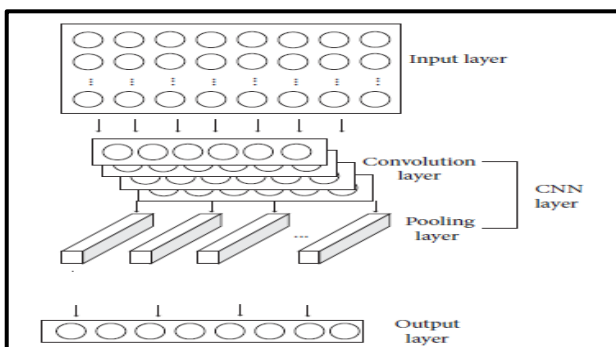

Fig 4. A simple CNN Architecture

The backpropagation process has been used to train the model in CNN model,The tuning parameters of the CNN:
- Number of hidden layers
- Number of neurons in each layer
- Learning rate
- Activation functions: ReLu, Sigmoid
- Epochs,

• Batch size, Optimization algorithms: are SGD, ADAM and RMSProp

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

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

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

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

III. ARIMA MODEL

Identification of Model

To fit any traditional time series model, the initial step is to check the stationarity condition. Stationarity can be determined from a time series plot which should show constant mean and variance. It can also be checked from an ACF plot. Specifically, very slow decay in the lags in ACF plots indicates a non-stationarity.

Testing Stationary of Time Series

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
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.
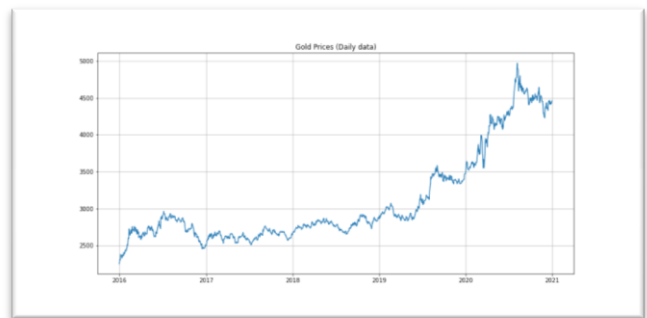
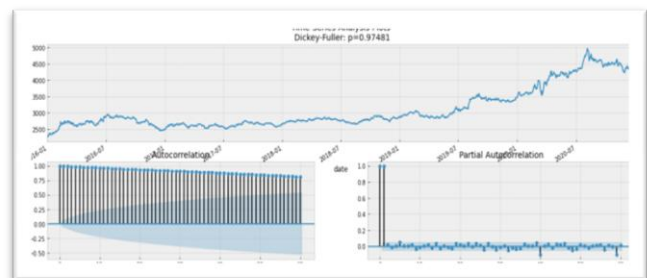

Figure 5: Time series plot of daily Gold Prices in India

Figure 6: ACF and PACF for daily Gold Prices in India

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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. The differencing method is used to convert non-stationarytime series into stationary time seriesof the data. In this paper, non seasonal difference of order 1 (i.e. d=1) is sufficient to achieve stationary in mean and variance. The derived variable .$W_t = \nabla^1 \hat{z}_t$ can now be examined for stationary.

Figure (7) 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.
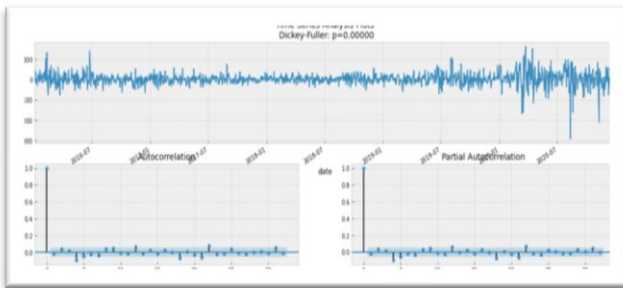

Figure 7: Time series plot,ACF and PACF of the first differences of daily Gold Prices in Indiaof the first differences of Daily Gold Prices in India.

Model Identification

This section shows how we determine the optimum 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. ACF and PACFare 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 (7), 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 superior 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	935.98	16.118	58.069	0	904.38	967.57

The fitted ARIMA model for the daily gold price in India is

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

Diagnostic Tests:

The autocorrelations and partial auto correlations of the residuals plots are used for diagnostic checking.
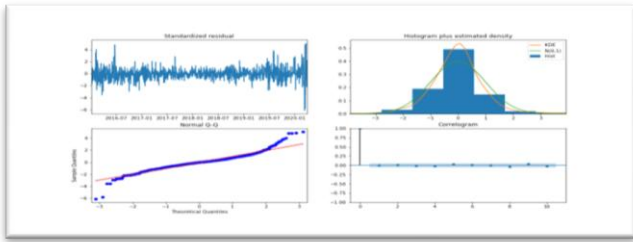
Analysis of Residuals

Figure (8): Residual Chart

Figure (8) show the estimated autocorrelation function for the residuals of theARIMA (2, 1, 2)model for the time series of daily Gold prices.

Box-Ljung Q- test statistic is used to test the adequacy of the model. The hypothesis on the model is below:

H0: The ARIMA (2,1,2) model is adequate.
H1: The model is ARIMA(2,1,2) 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

From the Table(4),the probability value of the test statistic is 0.81 which is greater than 0.05, therefore, we fails to reject Ho. Hence, we conclude that the ARIMA (2,1,2) model is an adequate model for the giventime series data.

IV. DEEP LEARNING MODELS

A. Multilayer Perceptron (MLP)

Python software has been used to train the MLP model on evaluate the model on test dataset.

Structure of the Network:

The MLP model consists of three: input layer, a hidden layer and an output layer. Two input neurons considered in this model, each representing the values of lag1 (previous day price in the same week i.e. lag1 gold price) and lag2 (lag 2 gold price). One output unit is needed in this modelwhich indicates the forecasts of daily gold price. Trial and error approach can be usedto find the optimal number of hidden units in the neural network. Typically we can use either the forward selection method or backward selectionto arrive the optimumthe hidden layer units. In the forward selection method, we choose a small number of hidden neurons then compute the network performance using RMSE, MAE and MAPE values. In the next step increment the hidden neuronsby one until train and test error is acceptably small or no further improvement is noted.

```
Model: "sequential"
_____
Layer (type)              Output Shape            Param #
=======================================================
dense (Dense)             (None, 500)             1500
_____
dense_1 (Dense)           (None, 500)             250500
_____
dense_2 (Dense)           (None, 1)               501
=======================================================
Total params: 252,501
Trainable params: 252,501
Non-trainable params: 0
```

B. Long Short-Term Memory (LSTM)

Python software has been used to train the LSTM model on evaluate the model on test dataset.

Structure of the Network:

```
Model: "sequential_1"
_____
Layer (type)              Output Shape            Param #
=======================================================
lstm (LSTM)               (None, 1000)            4008000
_____
dense_4 (Dense)           (None, 1)               1001
=======================================================
Total params: 4,009,001
Trainable params: 4,009,001
Non-trainable params: 0
_____
```

C. Convolutional neural networks (CNNs)

Python software has been used to train the CNNmodel on evaluate the model on test dataset.

Structure of the Network:

```
Model: "sequential_8"
_____
Layer (type)              Output Shape            Param #
=======================================================
conv1d_6 (Conv1D)         (None, 1, 64)           192
_____
flatten_5 (Flatten)       (None, 64)              0
_____
dense_17 (Dense)          (None, 500)             32500
_____
dense_18 (Dense)          (None, 1)               501
=======================================================
Total params: 33,193
Trainable params: 33,193
Non-trainable params: 0
_____
```

V. RESULTS AND DISCUSSION

The train dataset is used to train the models. Several traditional and deep learning models ARIMA, MLP, CNN and LSTM are examined.Once we trained the dataset using training dataset then we test the model on test dataset. The performance measures are showed in the Table5. Figures 9–12 represents the line charts of actual gold price and predicted gold prices.
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Table 5: Accuracy measures for different models to predict daily gold price (Rs/gram) in India

Forecasting Model	Error Measures	Train Set	Test set
ARIMA	MAPE	0.7	2.19
	RMSE	70.1	110.55
	MAE	21.68	97.07
MLP	MAPE	0.69	0.72
	RMSE	33.28	38.85
	MAE	22.13	31.21
CNN	MAPE	0.71	0.74
	RMSE	33.95	39.93
	MAE	22.66	32.23
LSTM	MAPE	0.65	0.69
	RMSE	31.46	35.87
	MAE	20.59	29.31

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The experimental results revealed that the LSTM model is the best among the four methods. In terms of forecasting performance measures, MAPE is 0.69, MAE is 29.31 and RMSE is 35.87, which is the lowest among the four forecasting models. Therefore, the LSTM model is superior to the other three comparative models in terms of forecasting gold prices in India.
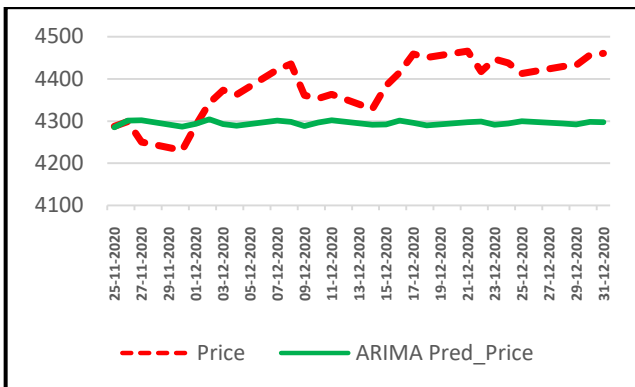

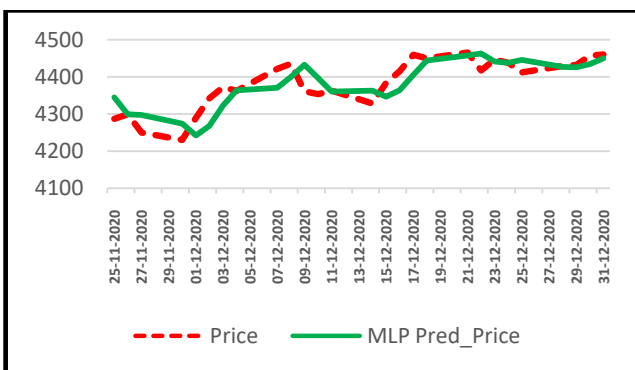**Figure. 9: ARIMA prediction (forecasted) of gold price(Rs/gram).**

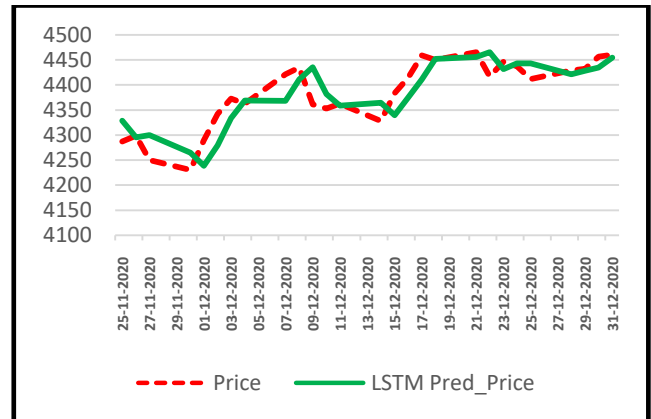**Figure. 10: MLP prediction (forecasted) of gold price(Rs/gram).**

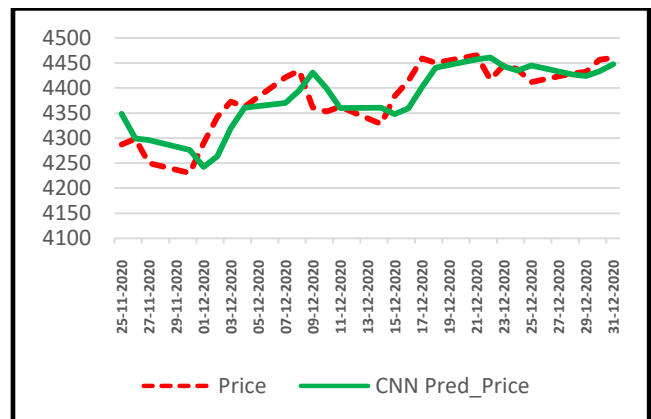**Figure 11: LSTM prediction (forecasted) of gold price(Rs/gram).**

Figure. 12: CNN prediction (forecasted) of gold price(Rs/gram).

VI. CONCLUSIONS

The main object of the paper is to compare the traditional time series models with deep learning algorithm. The historical data is collected from World Gold Council of gold prices in Rupees per gram, daily frequency ranging from January 2016 to December 2020. LSTM model outforms than other three modelsto forecast the gold price in India using historical data. This study is based on secondary data collected from. The analysis showed that the LSTM model has the lowestMAPE, RMSE and MAE and performed better compared with the traditional time series model like ARIMA, MLP and CNN.However, the model can be improved further by incorporate other factors such as US dollar, Crude oil, Inflation and Bank rates into the forecastmodel. Our future research work ismainly to incorporate some explanatory variables which are influences the gold prices to ensure the accuracy of gold forecast.Forecasts for test data using LSTM model presented in the following table (6).

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

Date	Price	Pred_Price	Date	Price	Pred_Price
25-11-20	4286.8	4328.7	15-12-20	4383.6	4339.7
26-11-20	4298.6	4295.0	16-12-20	4414.2	4374.3
27-11-20	4249.6	4299.6	17-12-20	4458.8	4410.9
30-11-20	4230.0	4264.7	18-12-20	4450.0	4452.2
01-12-20	4289.8	4238.2	21-12-20	4465.3	4455.9
02-12-20	4342.1	4279.5	22-12-20	4416.7	4465.5
03-12-20	4372.4	4333.6	23-12-20	4446.3	4431.8
04-12-20	4362.2	4369.1	24-12-20	4437.4	4443.2
07-12-20	4421.0	4368.3	25-12-20	4411.9	4443.3
08-12-20	4434.9	4411.0	28-12-20	4428.8	4421.6
09-12-20	4360.8	4435.4	29-12-20	4431.8	4428.6
10-12-20	4352.9	4381.8	30-12-20	4456.3	4434.9
11-12-20	4362.6	4358.5	31-12-20	4460.0	4454.4
14-12-20	4327.8	4364.1			

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