Traditional Arima, Lstm And Hybrid Techniques For Accurate Platinum Price Pridiction

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Abstract

Time series analysis becomes a vital tool in engineering, finance, and social research. Originally, univariate Autoregressive (AR) and univariate Moving Average (MA), Simple Exponential Smoothing (SES) model was developed to forecast next period data. Additionally, ARIMA was developed to deal with nonstationarity data. Specifically, the ARIMA model has shown superior accuracy and precision in forecasting the upcoming time series lags. Later, Artificial Neural Network (ANN) model and Long Short-Term Memory (LSTM) model are widely used in time series analysis for the different research areas. For predicting platinum prices, conventional mathematical model ARIMA and a non-linear method LSTM have been developed . Hybrid model has introduced in addition to LSTM model and ARIMA, conventional time series models.The primary goal of this study is to examine Hybrid capacity for modeling variations in the price of platinum and to assess how well it performs in comparison to other established time series modeling methods like ARIMA. Finally, based on performance standards including Mean Absolute Error(MAE), Root Mean Square Error(RMSE) the best-fit model is determined. Further the percentage better performance of the model is applied to test the accuracy of these models. The findings demonstrate that Hybrid technique is a potent tool for modeling the platinum price and can provide more accurate forecasts than LSTM and ARIMA model.

Key Words: Time series forecasting, ARIMA, LSTM, Hybrid, Error measures, Percentage better estimate.

1. Introduction

Platinum is a rarer and more valuable metal than gold. Globally, the metal is not easily accessible. Unlike gold, platinum is also employed extensively in manufacturing. This includes electronics, paint, and gasoline. Investing in platinum could be an excellent method of diversifying the holdings. The price fluctuates because of its many industrial applications. Platinum is really attractive at the moment. Changes in the global market affect the price of platinum in India because it is a commodity that is traded worldwide. Economic data, geopolitical events, and worldwide demand all have an impact on its price. Currency exchange rates, import taxes, and other local factors all have an impact on the price of platinum in the Indian market. Investors and consumers use these characteristics to gain a better understanding of the current and potential future values of platinum in India.

The Box-Jenkins Method, which incorporates the auto-regression model (AR), moving average model (MA), auto-regressive moving average model (ARMA), and auto-regressive integrated moving average model (ARIMA), is a widely used linear model from a classical standpoint. The traditional ARIMA model of the financial market is unable to describe the distribution of sequence of the nonlinear because of economy's rapid development of financial market.

As a result, several neural network models are widely used in various fields from an innovative standpoint. Because of its capacity to extract patterns from the nonlinear, nonstationary, and highly noisy time series data of stock prices, the artificial neural network (ANN) model has gained popularity. The animal brain's ability to handle complicated information through pattern recognition served as inspiration for the creation of the ANN model. ANN is an artificial intelligence technique that excels at data processing, fault tolerance, and model stationarity. Because it allows information to flow in multiple directions across its layers, the more complex Recurrent Neural Network (RNN) model gains popularity. Furthermore, in time series analysis, Long Short-Term Memory (LSTM), advancement over Recurrent Neural Networks (RNN), has shown promising results recently. We propose a hybrid approach that effectively leverages the capabilities of LSTM and ARIMA to maximize the prediction power of our models. In order to increase overall forecasting accuracy, this fusion seeks to use the complementary nature of these models. Because is so adept at finding complex patterns and nonlinear connections in datasets, it improves our prediction process. This fusion aims to leverage the complementary nature of these models to improve overall forecasting accuracy.

2. Methodology

2.1 Datasets

To investigate the patterns in the precious metal platinum prices of were collected from January 1st 2021 to 30th November 2023 (1064 observations) from website Rupeerates.in. ARIMA model and LSTM model will be applied to these data to forecast future platinum price trends. Determination of the model accuracy will be based on indicators Mean Absolute Error (MAE), Root Mean Score Error (RMSE).

2.2 ARIMA Model

ARIMA (p, d, q) is a model that combines AR, MA, and Integrated to forecast future values given a past value with a time sequence. As a result, d is the number of differences needed to render the time series stationary, p is the order of the AR term, and q is the order of the MA term. Stationarity results from the fact that ARIMA can only be used to predict the price of platinum if the time series is not seasonal and white noise. Since the MA model's future value is only dependent on the lagged forecast error and the AR model's is solely dependent on its lags, the future value of a variable in the ARIMA model is a linear combination of the random noise and the previous series value, which is represented as follows:

$$Yt = \alpha + \beta 1 Yt{-}1 + \beta 2 Yt{-}2 + \cdots + \beta p Yt{-}p + \varepsilon t + \phi 1 \varepsilon t{-}1 + \phi 2 \varepsilon t{-}2 + \cdots + \phi q \varepsilon t{-}q \qquad (1)$$

Here the variable values at time t are denoted by Yi, a constant by α, the autoregression coefficient by βi, the moving average coefficient by ϕi, and the random error at time t by εi.
The formula for the model may be shortened as follows:

$$\phi(B)\Delta^d y_t = \delta + \theta(B)\varepsilon_t \qquad (2)$$

where
$\phi(B) = 1 - \phi_1 B - \phi_1 B^2 - \ldots - \phi_p B^p$ and $\theta(B) = 1 - \theta_1 B - \theta_1 B^2 - \cdots - \theta_q B^q$

Consequently, the general procedures for forecasting future platinum prices include determining whether a time series is stationary and, if not, using differencing to make it stationary. The correct p, d, and q are then determined in order to construct the ARIMA model, which predicts the future platinum price. The final stage is to assess the model's accuracy. Four components of the modeling process are shown in the following flow chart.

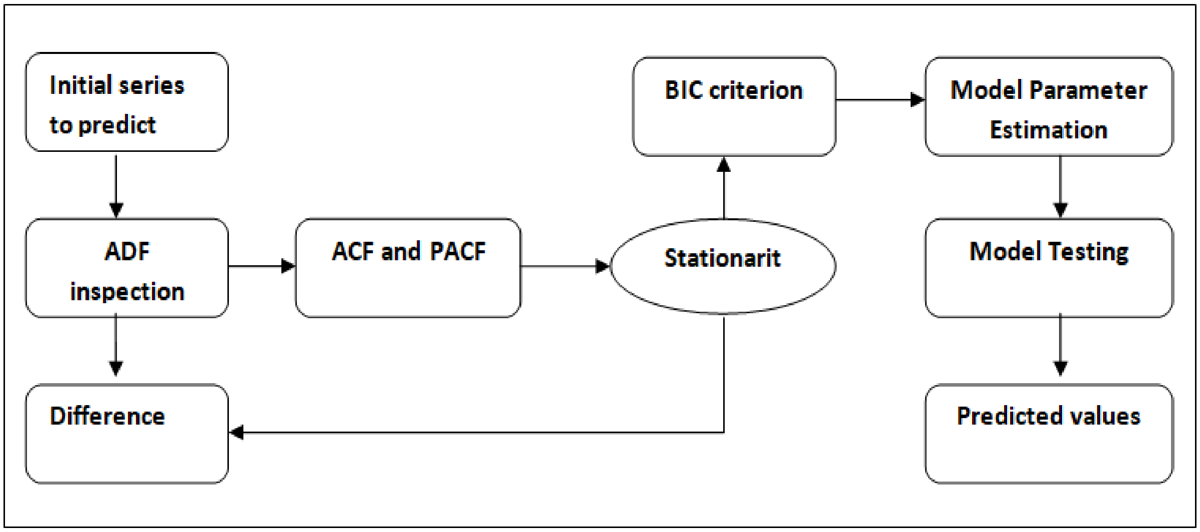

Figure 1: ARIMA Modeling Process

2.3 LSTM Model

The LSTM network is a novel sort of deep learning network that is a subset of RNN. In order to preserve the feedback error during gradient propagation, the LSTM network adds a memory module, which consists of one storage unit and three logic gates in each hidden layer neuron. This enhances the network's convergence and makes it more difficult for the network to fall into the local optimal solution. This is in contrast to the traditional RNN. Figure 4 shows the LSTM network construction. The input gate, forget gate, and output gate are the three logic gates, respectively.

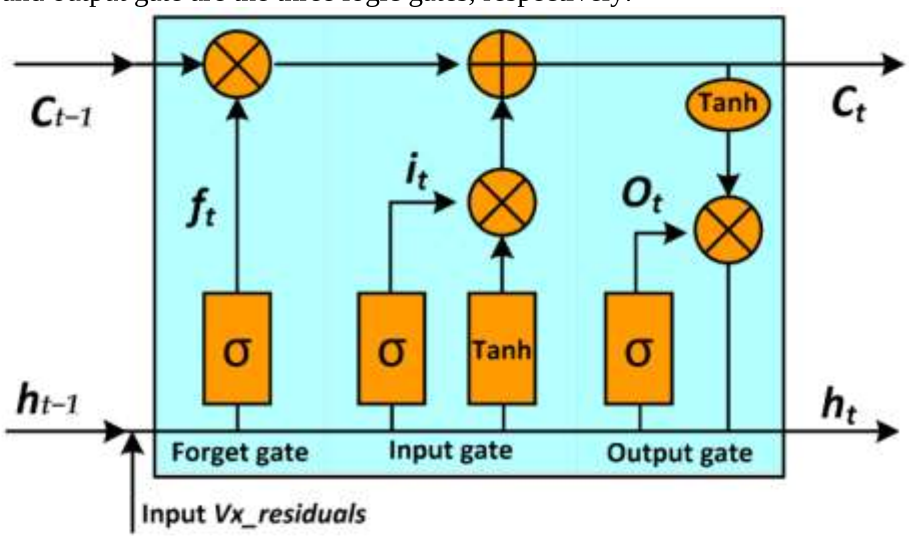

Figure 2: Basic Structure of LSTM

The recurrent neural network's hidden layer neurons are shown in Figure 4, and the network can learn long-term information thanks to the addition of the long and short-term memory module structure. The input layer and the output of the preceding memory module provide the current state data to the three logic gates of this memory module. They update the memory unit's current state by incorporating this data using a logic function (S-function). This neuron's state produces the following output:

$$c_1 = f_t c_{t-1} + i_t \tanh (W_{xc} V_{x\_residuals} + W_{hc} h_{t-1} + b_c) \quad (3)$$

where the output of the $t-1$th neuron is represented by c_{t-1} : and i_t are the input and forgetting gates' respective output results; The weight coefficients from the input layer to the present hidden layer are denoted by W_{xc}. The weight coefficients from the prior memory module to the current memory module are represented by W_{hc}, the output of the prior memory module is represented by h_{t-1}, and the bias term unique to the current memory module is represented by b_c.

2.4 Hybrid ARIMA – LSTM Model

It seems that not all time series will benefit from LSTM or ARIMA. Almost all real-world time series exhibit both linear and nonlinear correlation patterns between the data, which explains this. Zhang has devised a hybrid approach that uses ARIMA and LSTM separately to describe the linear and nonlinear components of a time series after recognizing this important problem. Zhang asserts that we possess:

$$Y_t = L_t + N_t + \varepsilon_t \quad (4)$$

where L_t,, N_t and ε_t represent the linear and nonlinear and error components, respectively, and Y_t represents the observation at time t. The analogous forecast at time t is obtained by first fitting the linear component using ARIMA. The residual at time t can therefore be found using the formula

$$e_t = Y_t - \hat{L}_t \quad (5)$$

Zhang asserts that as an ANN only contains nonlinear components, it can successfully predict the residuals data set following ARIMA fitting. With p input nodes, the LSTM for residuals has the following structure:

$$e_t = f(e_{t-1}, e_{t-2}, \ldots e_{t-p}) + \varepsilon_t \quad (6)$$

where ε_t is the white noise and f is a nonlinear function that the LSTM calculates. The final hybrid forecast at time t can be found as follows if the LSTM's forecast is:

$$\hat{Y}_t = \hat{L}_t + \hat{N}_t \quad (7)$$

Zhang empirically analyzed three real-world time series and found that his hybrid ARIMA-LSTM technique greatly outperforms both ARIMA and ANN models in terms of prediction accuracy.

3. Comparison of the Model performance

3.1 Error Metrics

The forecasting models is assessed using metrics called Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE). These measurements of Absolute Value of Errors (MAE) and Root of the Mean of the Square of Errors (RMSE) let us know how accurate our predictions are and how far they deviate from the real numbers. The disparities between the actual values of a variable and the projected values—values that our predicted model are referred to as errors in this context. They are computed as

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{y}_i - y_i\right)^2} \quad (8)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \widehat{y_i}|$$

where,

n: *number of observation*

y_i: *the actual value of the i^{th} observation*

$\widehat{y_i}$: *the predicted value of the i^{th} observation*

3.2 Percentage Better performance of the model

The degree to which one model outperforms another is indicated by the percentage improvement in model performance. Usually, measurements like accuracy, root mean square error (RMSE) mean absolute error (MAE), R-squared, or any other performance statistic pertinent to your issue are used to compute this.

$$\text{Percentage Improvement} = \frac{P_{new} - P_{old}}{|P_{old}|} \tag{9}$$

where P_{new} is the performance metric of the improved model

P_{old} is the performance metric of the base model.

4. Analysis of Platinum Price Prediction

4.1 Forecasting by ARIMA

There are basically four processes involved in creating an ARIMA model for any variable: forecasting, diagnostic evaluation, estimation, and identification. Box-Jenkins methodology's fundamental steps are outlined here.

Examining the data on platinum prices Figure 1 shows a non-stationary characteristic of the time series from January 1, 2021, to November 30, 2023. As seen in Figures 2 and 3, the ACF and PACF measurements for stationarity also suggest that the time series is not stationary. As a result, until the ARIMA model becomes stationary, it cannot be used directly. Figure 4 illustrates how the new time series becomes more stationary after a single time difference. The new time series' stationarity is demonstrated by the ACF and PACF in Figures 5 and 6. Because the time series becomes stationary after the first difference, d for ARIMA will therefore equal 1.

Figure 3: Time series of daily platinum prices(Rs/gram) in India

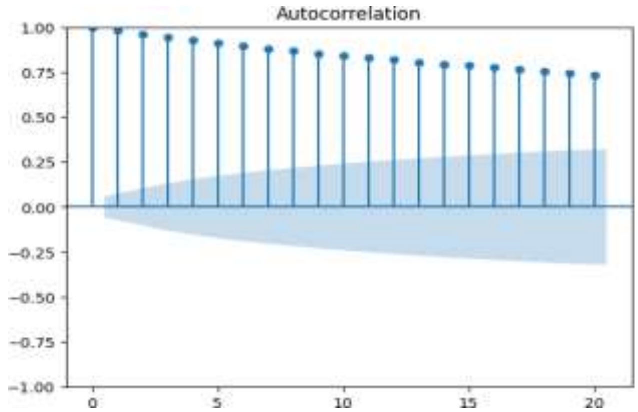

Figure 4: Sample ACF before differencing

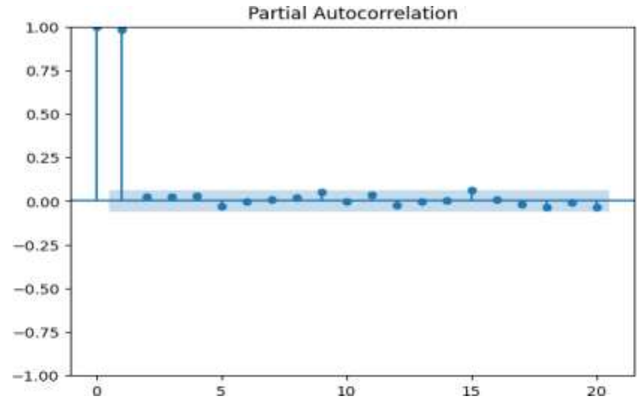

Figure 5: Sample PADF before differencing

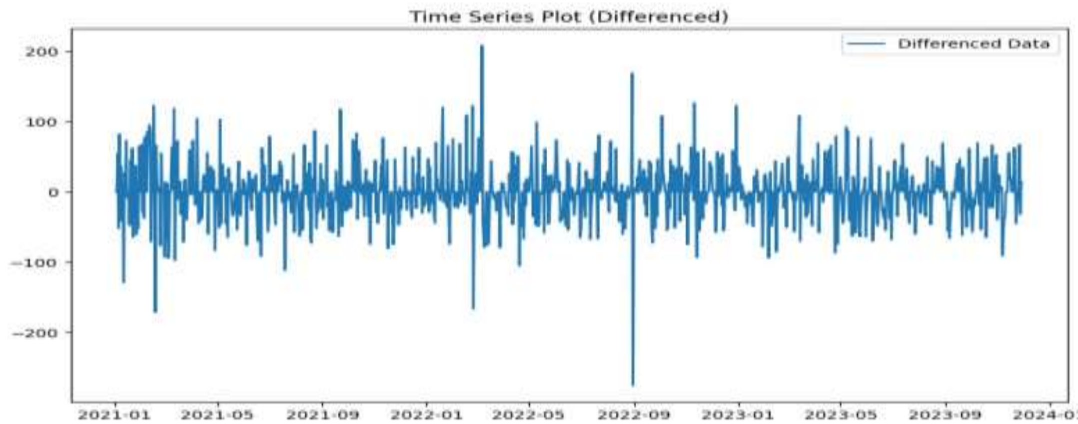

Figure 6: Time plot for Trasformed series

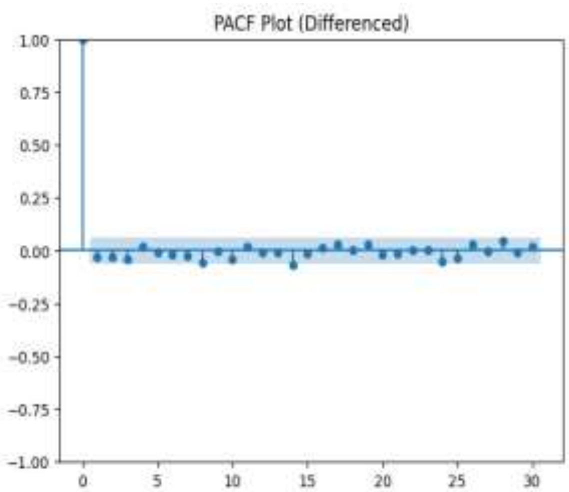

Figure 7: Sample ACF after differencing

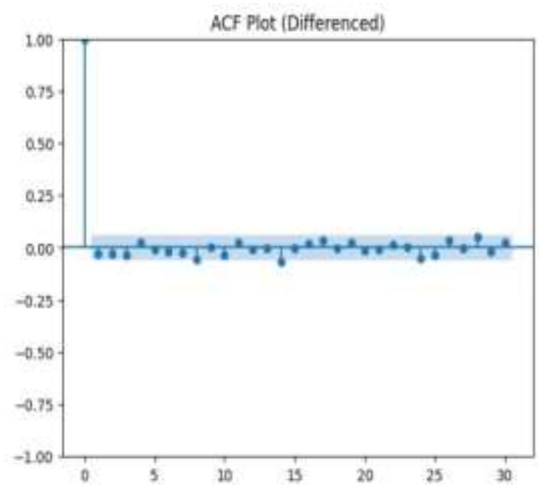

Figure 8: Sample ACF after fferencing

The model that fits the data the best for predicting platinum prices is the ARIMA (0, 1, 1) model. Due to its inability to provide enough information for intricate forecasts, ARIMA (0, 1, 1) is less useful for predicting platinum prices. for complex predictions. In order to forecast the daily platinum prices in India, the model was created as

$$\nabla^d \ln Z_t = (1- 0.039B^1) \quad (10)$$

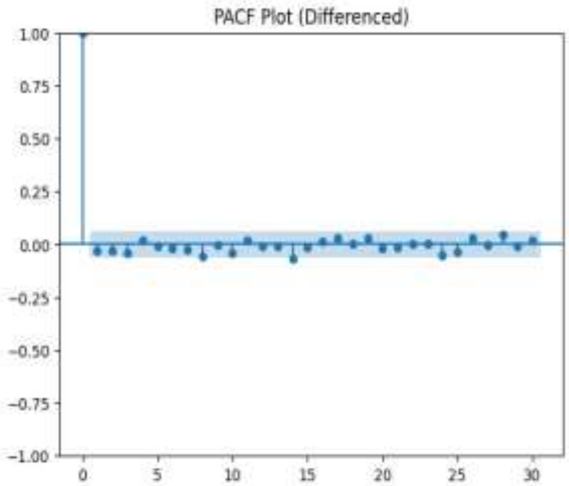

Figure 7: Sample ACF after differencing

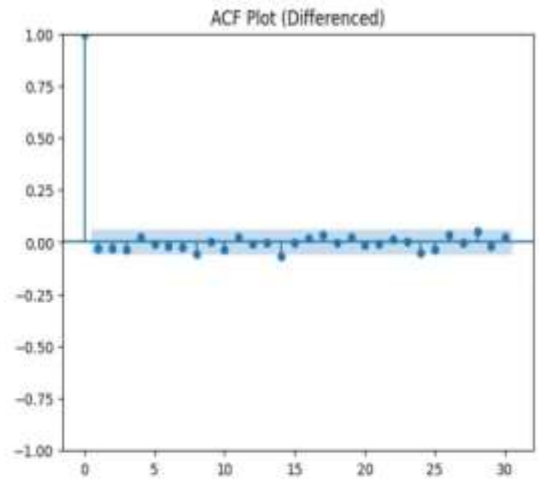

Figure 8: Sample ACF after fferencing

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The comparison between the ARIMA model's predicted results and actual platinum prices is shown in Figure 9.

Figure 9: Forecasting based on ARIMA (0,1,1)

4.2 Forecasting by LSTM

After applying the fundamental LSTM model to the dataset, 30% of the data is chosen as the test set and the remaining 70% as the training set. As indicated by Equation (4), the Min-Max Normalization approach is used to normalize both the training and test sets. Consequently, normalizing preserves the range and periodic information. Additionally, normalization can increase training efficiency and speed up the process of finding the best option. After normalization, LSTM model is constructed for the specified LSTM variable. The model's strong robustness is demonstrated by the good convergence of the train and test data loss functions, as seen in Figure 9. Thus, the platinum price data may be subjected to the simple LSTM model to get the prediction results that are displayed in Figure 10.

$$x' = \frac{x-\min(x)}{\max(x)-\min(x)} \quad (11)$$

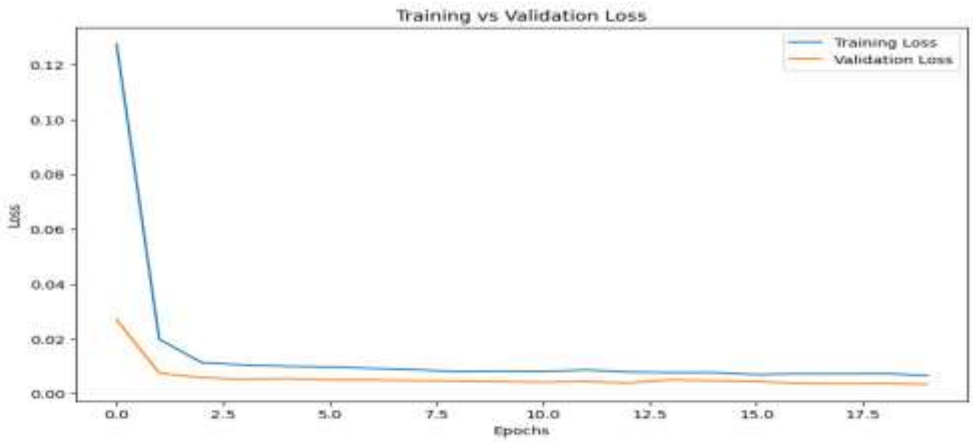

Figure 10: Loss Function

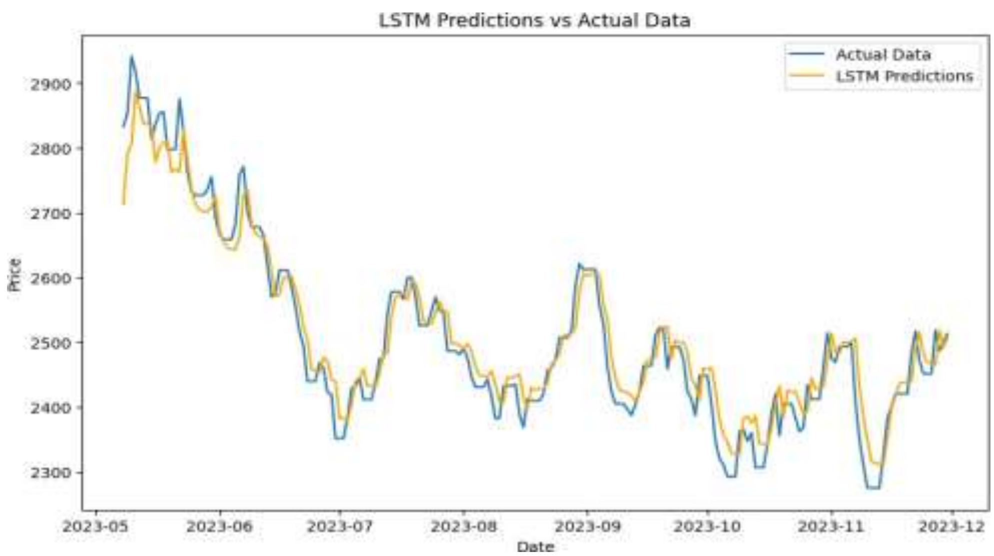

Figure 11: Forecasts based on LSTM

However, even if the findings show that the fundamental LSTM model predicts the price of platinum with a comparatively high degree of accuracy, the performance can be shown as overfitting, which leaves out important details for developing a practical plan.

4.3 Forecasting by HYBRID

For creating the hybrid model, the linear component of the ARIMA model can be used, and the residuals from the linear model will then only include the nonlinearity connection. Once the predicted values for the linear component values of ARIMA of (0, 1, 1) have been determined, the residual values are added to the LSTM model The LSTM model for residuals is built with specified number of variables and since the chosen network has the lowest MAE, MAPE, and RMSE. The model's strong robustness is demonstrated by the good convergence of the test data loss functions, as seen in Figure 12. Thus, the platinum price data may be subjected to the LSTM model to get the prediction results that are displayed in Figure 13.

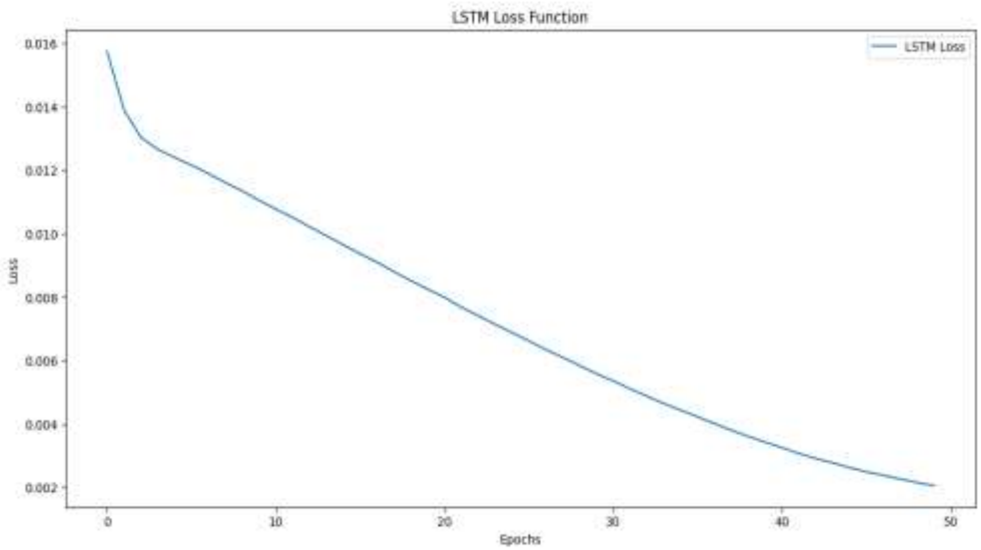

Figure 12: Loss Function for Hybrid model

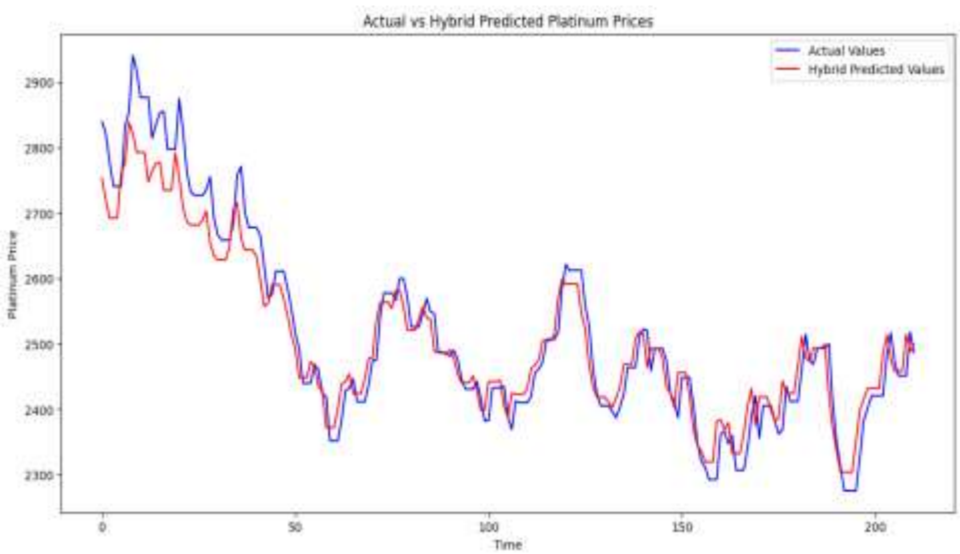

Figure 13: Forecasts based on Hybrid model

5. Comparison of ARIMA and LSTM

In terms of metrics RMSE and MAE, Table 1 displays the prediction performance outcomes for the ARIMA and LSTM models. According to table 1 below, the LSTM model has done better than other model in terms of error measures. In other words, ARIMA model would not be able to capture all of the patterns in the data.

Model	RMSE	MAE
ARIMA	118.19	88.52
LSTM	42.65	32.24
HYBRID	36.87	28.53

Table 1: Forecasting performance of ARIMA and LSTM

The following table displays the two models percentage better estimate of statistical findings.

Model	Base Method		
	ARIMA	LSTM	HYBRID
ARIMA	*	65.22	63.67
LSTM	46.589	*	79
HYBRID	58	70	*

Table 2: Percentage better performance

Table 10 demonstrates the superior performance of LSTM over ARIMA models. Overall, the LSTM model outperforms the ARIMA model. Therefore, when compared to ARIMA and LSTM model is the most appropriate model for predicting platinum prices.

6. Conclusion

In this study, the effectiveness of various approaches for predicting changes in the price of platinum was examined. Traditional time series forecasting and deep learning forecasting can be two categories of financial time series analysis. These days, forecasting makes extensive use of hybrid models, which blend one or more model types. Both linear and nonlinear forecasting models frequently use them. Hybrid models frequently produce better overall prediction results than single forecasting models, even when single models may be accurate during certain prediction periods. There are increasing opportunities to combine single and hybrid models to improve forecasting accuracy. . The performance of the traditional ARIMA model, deep learning LSTM model and Hybrid model on predicting the Platinum price of India from January 1st 2021 to 30th November 2023 are examined using performance evaluation metrics RMSE and MAE. The result shows that Hybrid gains a higher accuracy than LSTM and ARIMA in platinum price prediction. Results of this study reveals that Hybrid model is 79% better model than LSTM and 70 % better model than ARIMA model Therefore the suitable model for prediction of Platinum prices is Hybrid model. Using Hybrid model to increase predicting accuracy yielded the most significant findings.

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