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Analysis of Quantum Trading Strategy Algorithms: LSTM and ARIMA

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Algorithmic trading has transformed financial markets by harnessing computational power. This has enabled traders to make faster, more accurate decisions and execute trades in real time. It has also enabled high-frequency trading, which results in increased market volatility. Trading decisions on financial markets are automated using computer algorithms like LSTM and ARIMA to examine algorithmic trading principles and strategies at the intersection of finance and technology. To manage risk and optimize trade execution, the algorithm leverages market inefficiencies. It highlights the importance of addressing algorithmic trading in today's financial market and provides recommendations for future research in the stock market domain. A hedged investment (which reduces risk) contributes to long-term profit. Experimental analysis can be made to compare LSTM and ARIMA based on MSE values. Due to its ability to capture time series dependencies, LSTM is particularly useful for daily forecasting because it can capture long-term dependencies. Meanwhile, ARIMA is best suited for forecasting monthly and weekly patterns because it models and forecasts seasonal patterns.

Keywords: Hedging, Stock price, LSTM, ARIMA, Quantum trading.

1. Introduction

Stock trading broadly refers to stock buying and selling. Stock trading is a challenging and risky enterprise, but by continuously learning, we can lower risks and increase success. This work can be done with a model that employs computer programmers and algorithms. [11] Quantitative trading is the process of identifying and profiting from trading opportunities using simple or complex mathematical models Quantitative trading also involves the analysis of market data and using that data to develop trading models and make predictions about future market movements. These models can be back tested on historical data to identify potential trading opportunities.

Traditionally, Data analysis using time series techniques are 1) linear regressions to fit models, 2) MA which is the "moving average" for predicting time series data. These techniques are known as "ARIMA (Auto Regressive Integrated Moving Average)". The development of linear regression over the years has led to a number of improvements, this model has been modified in several ways, including SARIMA (or Seasonal ARIMA), and ARIMAX (or

ARIMA with Explanatory Variables). [1] Models such as these perform reasonably well for long-term forecasts, but badly for short-term forecasts.

An emerging technique in AI-driven data analysis is machine learning and deep learning. [12] By leveraging learning and artificial intelligence, data analytics processes are taken to an entirely new level. [17] It is possible to train the most appropriate learning model based on the underlying application domain. In image recognition, convolution-induced neural networks (CNNs) are suitable; in time series data modeling, recurrent neural networks (RNNs) are better suited.

An RNN-based model can be categorized into several variations. [19] The main difference between these RNN-based models is their ability to remember input data. Generally, vanilla RNNs cannot remember past data. [26] The term feed-forwarding-based learning mechanism refers to these representations in deep learning terminology. [2] The Long Short-Term Memory (LSTM) network is a special type of RNN that models relationships between longer inputs and outputs. By employing several gates into their network architecture, RNN-driven models can be learned from past data, which allows them to construct a predictive model while retaining the past data. This results in single traversal of the input data. Forecasting time series and long-term prediction problems with conventional ARMA models and deep learning algorithms.

Even though ARIMA is superior to LSTM for long-term predictions and LSTM is for short-term prediction. In the rest of the paper, the following structure is followed. A description of the research methodology is provided in Section 2. Furthermore, this section includes detailed descriptions of models and information, along with pseudocodes of algorithms.[22] The dataset description and assessment metrics are outlined in Section 3. [18] The diagnosis is presented in Section 4 along with a comparison and validation of the results. Finally, Section 5 summarizes the paper's findings and gives a glimpse of the future.

2. Research Methodology:

This section outlines the experimental methodology adopted for the stock market data. Algorithms like LSTM and ARIMA process real-time data by passing appropriate parameters. [3] MSE (Mean square error) values are measured and compared to find the most appropriate result.

A. An Autoregressive-Integrated-Moving-Average- Model

Combining AR and MA processes, the ARIMA model produces a composite form. ARMA, or Auto- Regressive-Moving-Average, is a generalized variant. As the ARIMA model fully captures all of the model's essential components (a, b, and c):

Auto-regression is the relationships between information and (a) the number of lag observations are obtained using the regression model AR. [11] By using integrated relationships to measure the variances between observations made at various times (b), the time series was made stationary.Moving average MA is used to analyze lag-timed data, it is possible to consider the dependence between the data and the error values (c).

[6] The linear process form may be used to express an autoregression (AR) model of order in

its simplest form, denoted as AR(a):

$$X_n = K + \sum_{i=1}^{p} \emptyset_i . x_{n-1} + \epsilon_n \tag{1}$$

Where Xn in equation(1), is the static variable, k is the numerical constant value, the variable $\emptyset i$ is the repeated function that automatically correlates at the lags 1,2,.3,.., p and, the Gaussian function having the noise that also has white series with mean function with the value as zero and the variance. [25] An MA model having the function ordered as c,

MA(c), denoted as:

$$X_n = M + \sum_{x=0}^{c} \theta_x . \epsilon_{n-x} \tag{2}$$

Where, M in the above equation(2), is the expected term of Xn that is zero, the θx values are the weights measured by the values of the probability of the series having time valuation term, and θ1 = 1. [20] Then the ϵn is a Gaussian model with a noise value of white and having a null mean and then the varianceσ2. Then merge the AR has a and MA has c models by combining both of the models organized and providing an (a,c)

ARIMA model:

$$X_m = K + \sum_{j=0}^{a} d_j . x_{m-j} + \in_m + \sum_{j=0}^{c} \emptyset_j . \epsilon_{m-j} \tag{3}$$

Here, in equation(3),the AR and MA parameters a and c are in order, due to its "integrate" stage. A method of differentiating the time series is used in the "integrate" component's instance to make an anti-stationary time series static and stationary [5]. ARIMA' model has seasonal evaluation prediction done with data analysis on a time base, and the better the model is made up of non-seasonal components in one way or another. [10] Since both seasonal and non- seasonal elements must be taken into account in a multiplicative model, we must constructed the seasonal ARIMA model [14].

It is possible to visualize the seasonality of the ARIMA model as ARIMA (a, b, c) x (A, B, C)X. Here a refers to the nonseasonal Auto Regressive model, b is used to refer to the nonseasonal deviation, c is used to refer to the nonseasonal Moving Average model, A is used to refer to the seasonal Auto Regressive model, B is used to refer to the seasonal model of differencing, C is used to refer to the seasonal Moving Average model, and at last X is used to refer to the time series of regressive seasonal patterns of data respectively [24]. The most and at the end the most important thing is to step in evaluating the seasonal deviations in the ARIMA' which is used to identify the standards of (a, b, c) and (A, B, C)X. [16] For example, the variance increases with time as seen by the time stamp value for the graphic of the inactive data should utilize the stable variance that gets the conversions approach and the method of variations [21]. The Partial-Auto- Correlation-Function (PACF) to establish that many c means moving averages are required for the calculation, the Auto-Correlation-Function (ACF) is used to figure out the value of undeviating components between findings we have taken in a timely data record that deviated from a time lagging point a, and Inverse- Auto-Correlation-Function (IACF) to detect over differencing, The a base values of the autoregressive model, the b model of differencing, the c value of the moving average [9]. The differencing parameter, which converts it, is possible to convert timely data that is not static into a static one in the order of the difference frequency b.

B. Long Short-term Memory (LSTM)

LSTMs are extensions of RNNs, which solve the vanishing gradient problem very efficiently. As LSTMs extend RNN memories, they learn long-term dependence between inputs and keep track of them. [4] Consequently, they can read, write, and delete information from their memories over an extended period. "Gated" cells in LSTM memory refer to the ability to preserve or ignore memory information based on the gate decision. [9] Long-term memory LSTM models capture and preserve important features from inputs. To decide whether to delete or preserve information, weight values are applied during training. Hence, an LSTM model learns what information is worth preserving or removing.

An LSTM model consists of three gates: forget, input, and output. [15] Input gates determine how much-added information will be stored in the memory; output gates determine whether the existing value in the cell contributes to the output.

I) Forget Gate. To determine what information needs to be removed from the LSTM memory, this gate usually employs a sigmoid function. [24] Decisions are essentially made based on value of hgn-1 and Yn. fgn, in the equation(4), the gate's output, ranges from 0 to 1, where 0 indicates that the learned value has been completely discarded, while 1 indicates that the learned value has been preserved. In order to compute this output,

$$fg_n = \sigma(W_{fhg}[hg_{n-1}], W_{fxg}[Y_n], B_{fg}) \quad (4)$$

Bfg represents the bias value and is a constant.

II) Input Gate: The input gate determines whether new information should be added to the LSTM memory. It is composed of two layers: one sigmoid layer and one "tanh" layer. The sigmoid layer determines which values should be updated. An LSTM memory is updated by adding new candidate values from the tanh layer.

$$i_n = \sigma(W_{ihg}[hg_{n-1}], W_{ixg}[Y_n], B_i) \quad (5)$$

$$C^{\sim}_{n} = tanh(W_{chg}[hg_{n-1}], W_{cxg}[Y_n], B_c) \quad (6)$$

Here, equation(5), in indicates whether the value needs to be updated, and in equation(6), $C\sim$ this vector indicates the new candidate values that will be added to the LSTM memory. With these two layers combined, the current value of the LSTM memory is forgotten using the forget gate layer. The old value is multiplied by this new value (i.e., $Ct-1$) next, update the candidate value $in * C\sim$. Mathematics can be represented by the following equation(7)

	$C_n = f_n * C_{n-1} + i_n * C_n^{\sim}$	(7)

Here, fn is an outcome of a forget gate is a value between 0 and 1, where 0 denotes complete erasure, and 1 denotes complete preservation.

III) Output Gate: The gate determines which part of the LSTM memory contributes to the output using a sigmoid layer. [7] After mapping the values between 1 and1, the nonlinear tanh function is applied. The result is finally multiplied by the output of the sigmoid layer. This equation represents the formula for computing the output:

	$O_n = \sigma(W_{ohg}[hg_{n-1}], W_{oxh}[Y_n], B_o)$	(8)
	$h_n = O_n * tanh(C_n)$	(9)

Here, in the above equation(8), represents the output, and hn in the equation(9), corresponds to its expression between −1 and 1.

3. LSTM VS. ARIMA: AN EXPERIMENTAL STUDY

This paper compares the performance of ARIMA and LSTM, in the context of predicting financial time series

A. Data Set

The data is fetched directly from Yahoo Finance in real time. In this experiment, ARIMA and LSTM algorithms were compared using these data. From the listed date to today's market trend, the data is selected from the Yahoo finance site. [8] Every eight hours, these market values are updated. In those algorithms, five shares of five companies are loaded and they are TCS, Tesla, Meta, KM Sugars, and Sun Pharmaceutical. [23] The data feed provides input data that is used to receive updated data from data sources.

B. Testing and training data

ARIMA and LSTM models were developed with the "Adjusted Close" variable of the financial time series. The data set was divided into training and testing. 80% of each data set was used for training and 20% for testing model accuracy.

C. Metrics

Deep learning algorithms typically report "loss" values. An incorrect prediction results in a loss. It is more accurate to say that if the model predicts perfectly, there will be no loss value. Try to obtain weights and biases that minimize loss values to minimize loss values. RMSE is used as a measure of prediction performance alongside loss, which is used by deep learning algorithms. Differences between actual and predicted values are measured by RMSE.

$$RMSE = \sqrt{\frac{1}{T}\sum_{i=1}^{T}(x_i - \hat{x})^2} \quad (10)$$

Where, in the equation(10), refers to the total number of observations. The actual value xi is the actual value, while the $\hat{xi}$ is the predicted value. RMSE penalizes large errors. In addition, scores are scaled in the same units as forecasts. [13] As a further measure of improvement, we also calculated the percentage reduction in RMSE.

$$Difference\% = \frac{observed\ value - Existing\ value}{Existing\ value} * 100 \quad (11)$$

Here, in equation(11), the percentage of difference is calculated with the observed value and existing value to know the deviation between the observed results.

4. Experimental Results:

Stock price prediction using the LSTM and ARIMA models for five companies. There is a close match between the two models in terms of results.

Table.1 Comparative analysis of TCS stocks with LSTM and ARIMA based on MSE values has the stock name, start date from the year 2015 and end year 2022, then the different number of LSTM execution and MSE of LSTM and MSE of ARIMA. That shows the long periods have the MSE value on LSTM is high when it is compared with the ARIMA.

Table.1. Comparative analysis of TCS stocks with LSTM and ARIMA based on MSE values

Stock Name	**Start date**	**End date**	**LSTM Executions**	**MSE of LSTM**	**MSE of ARMA**
TCS	2015-01-01	2022-12-15	10	0.0317107360	0.0003702251
			25	0.0295844419	
			50	0.0264422612	
	2016-01-01	2022-12-15	10	1.360662e-02	5.614322e-06
			25	1.343014e-02	
			50	1.326300e-02	
	2017-01-01	2022-12-15	10	4.979803e-03	1.057833e-05
			25	4.647294e-03	
			50	4.154878e-03	
			100	3.378103e-03	
			200	2.486930e-03	
	2018-01-01	2022-12-15	10	8.051768e-03	2.736256e-05
			25	8.906338e-03	
			50	1.165662e-02	
	2019-01-01	2022-12-15	10	1.533054e-03	1.948472e-05
			25	1.741373e-03	
			50	2.117371e-03	
	2020-01-01	2022-12-15	10	1.905887e-03	3.563358e-05
			25	1.911220e-03	
			50	1.924284e-03	

	2021-01-01	2022-12-15	10	0.0059785844	0.0003292726
			25	0.0058699433	
			50	0.0056847680	
	2022-01-01	2022-12-15	10	0.001458689	2.001337994
	2022-05-01	2022-12-15	10	0.0007284252	3.0004097360
	2022-10-01	2022-12-15	10	0.0004856600	1.0002975625
	2022-12-01	2022-12-15	10	0.00148329	1.002500

While comparing with daily basis calculation, the MSE values in LSTM are less when it is compared with ARIMA values.

Where Figure 1, shows the 8 years data of TCS stock price in a graph and its difference between ARIMA prediction vs LSTM prediction and real price this shows the values deviation in a graph. In figure 2, shows the TCS stock data of same 8 years data MSE values deviation in graph.

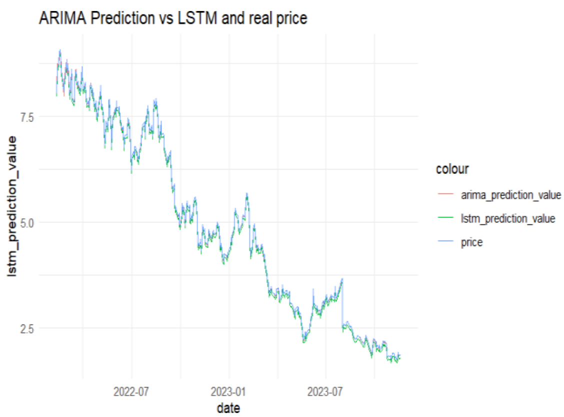

Figure 1. TCS 8 years data of LSTM vs ARIMA vs Real price.

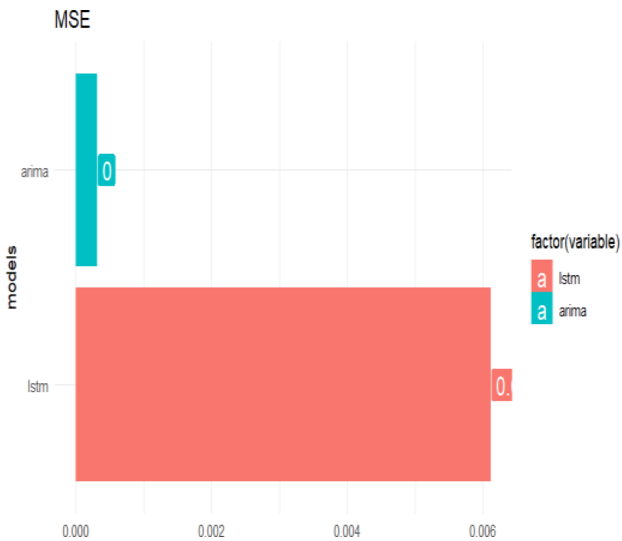

Figure 2. TCS 8 years data MSE value of LSTM vs ARIMA

Here Figure 3, shows the 51 days of TCS stock price in a graph and its difference between ARIMA prediction vs LSTM prediction and real price this shows the values deviation in a graph. In figure 4, shows the TCS stock data of same 51 days data MSE values deviation in graph.

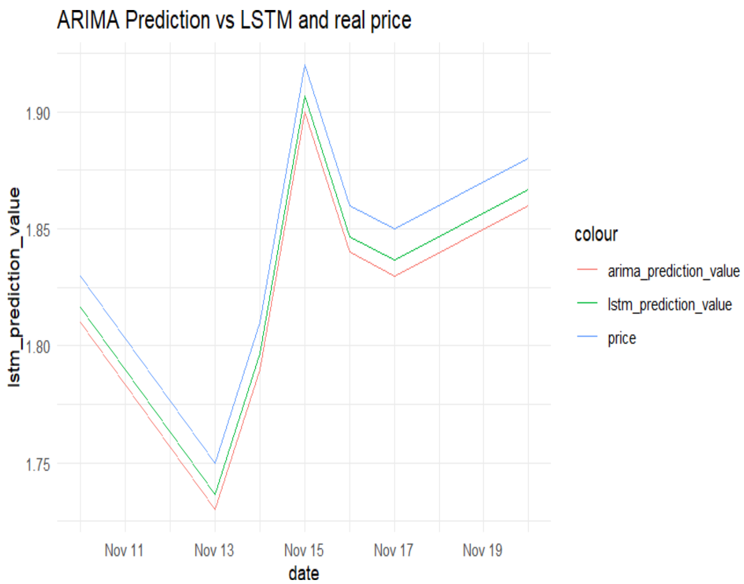

Figure 3. TCS 51 days data of LSTM vs ARIMA vs Real price.

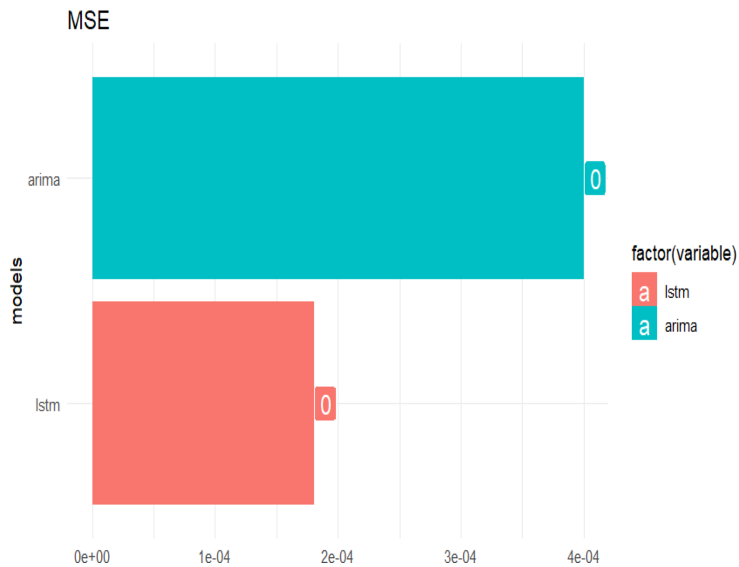

Figure 4. TCS 51days data MSE value of LSTM vs ARIMA.

Table.2 Comparative analysis of Tesla stocks with LSTM and ARIMA based on MSE values has the stock name, start date from the year 2015 and end year 2022, then the different number of LSTM execution and MSE of LSTM and MSE of ARIMA. That shows the long periods have the MSE value on LSTM is high when it is compared with the ARIMA.

Table.2. Comparative analysis of Tesla stocks with LSTM and ARIMA based on MSE values

Stock Name	Start date	End date	LSTM Executions	MSE of LSTM	MSE of ARMA
TSLA	2015-01-01	2022-12-15	10	32.18315962	0.01309571
			25	31.41911107	
			50	30.15195571	
	2016-01-01	2022-12-15	10	1.64887764	0.02099499
			25	1.67922682	
			50	1.73986906	
	2017-01-01	2022-12-15	10	0.54738609	0.04211514
			25	0.57036904	
			50	0.60402454	
	2018-01-01	2022-12-15	10	11.443881	0.083509
			25	11.932296	
			50	12.786269	
	2019-01-01	2022-12-15	10	0.5336736	0.3520316
			25	0.5257232	
			50	0.5002769	
	2020-01-01	2022-12-15	10	51.3106907	0.3520316
			25	51.6247231	
			50	52.1117487	
	2021-01-01	2022-12-15	10	5.5090678	0.3520316
			25	5.4485783	
			50	5.3448632	
	2022-01-01	2022-12-15	10	11.8542365	0.7028465
	2022-05-01	2022-12-15	10	5.800928	1.254424
	2022-10-01	2022-12-15	10	2.439658	1.404219
	2022-12-01	2022-12-15	10	13.23612	14.56001

Where Figure 5, shows the 8 years data of Tesla stock price in a graph and its difference between ARIMA prediction vs LSTM prediction and real price this shows the values deviation in a graph. In figure 6, shows the TCS stock data of same 8 years data MSE values deviation in graph.

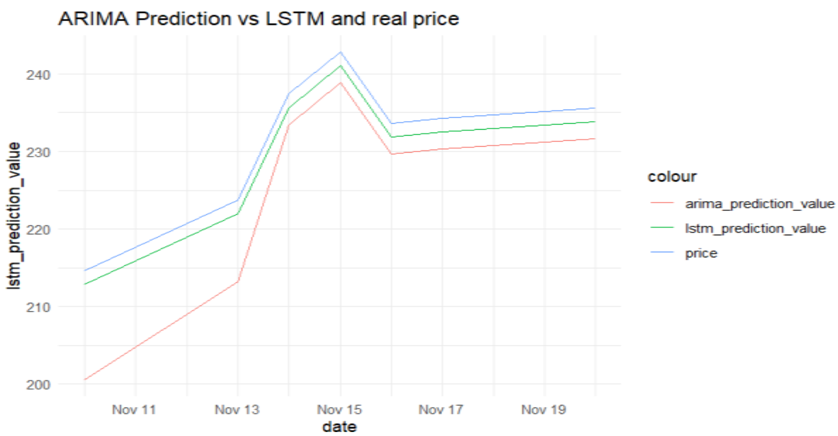

Figure 5. Tesla 8 years data of LSTM vs ARIMA vs Real price.

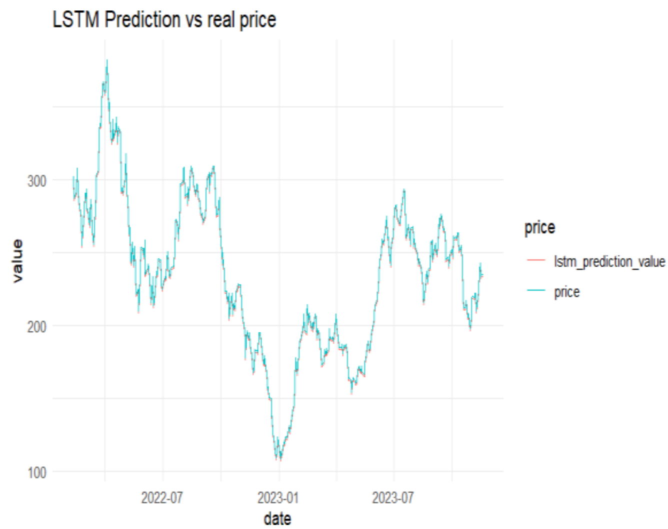

Figure 6. Tesla 8 years data MSE value of LSTM vs ARIMA.

Here Figure 7, shows the 51 days of Tesla stock price in a graph and its difference between ARIMA prediction vs LSTM prediction and real price this shows the values deviation in a graph. In figure 8, shows the Tesla stock data of same 51 days data MSE values deviation in graph.

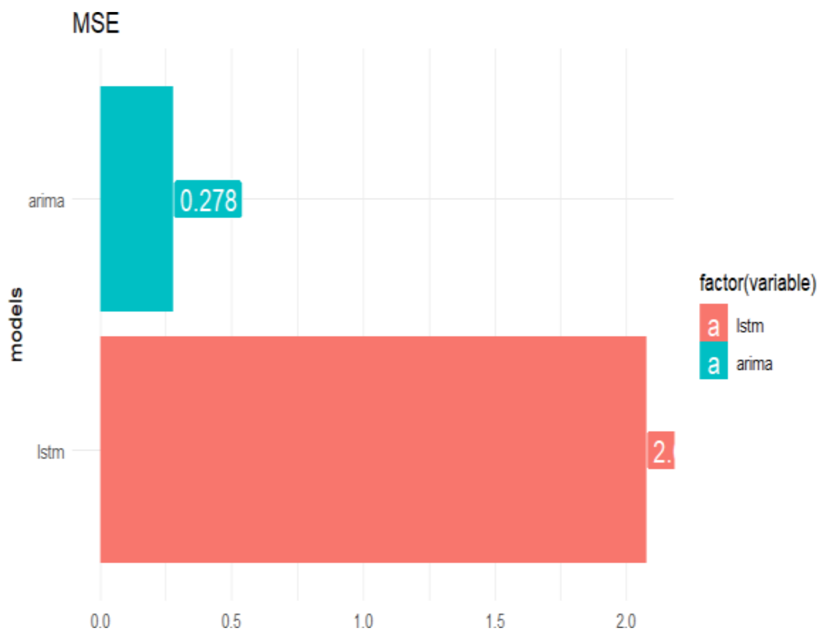

Figure 7. Tesla 51 days data of LSTM vs ARIMA vs Real price.

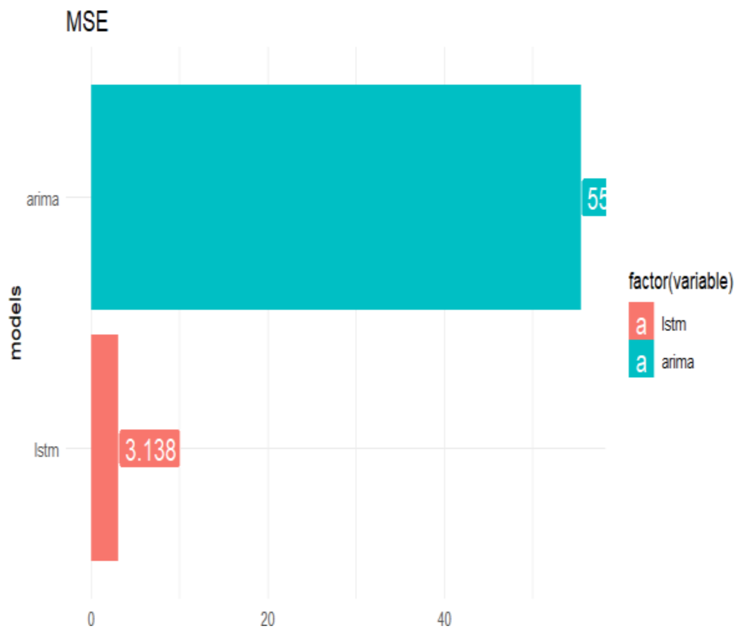

Figure 8. Tesla 51days data MSE value of LSTM vs ARIMA

Table.3 Comparative analysis of Meta stocks with LSTM and ARIMA based on MSE values has the stock name, start date from the year 2015 and end year 2022, then the different number of LSTM execution and MSE of LSTM and MSE of ARIMA. That shows the long periods have the MSE value on LSTM is high when it is compared with the ARIMA.

Table.3. Comparative analysis of Meta stocks with LSTM and ARIMA based on MSE values

Stock Name	**Start date**	**Today**	**LSTM Executions**	**MSE of LSTM**	**MSE of ARMA**
META	2015-01-01	2022-12-15	10	0.05394755	0.02371288
			25	0.04483532	
			50	0.02829912	
	2016-01-01	2022-12-15	10	2.33067642	0.03815103
			25	2.26174192	
			50	1.326300e-02	
	2017-01-01	2022-12-15	10	2.15663425	0.03815103
			25	17.01218188	
			50	17.0794519	
	2018-01-01	2022-12-15	10	0.16277582	0.02252768
			25	0.12086372	
			50	0. .06692626	
	2019-01-01	2022-12-15	10	0.349914877	0.009174279
			25	0.258158148	
			50	0.139888624	
	2020-01-01	2022-12-15	10	4.220770763	0.001910895
			25	4.119331271	
			50	3.944135438	

	2021-01-01	2022-12-15	10	0.46267086	0.06689877
			25	0.48128182	
			50	0.52803186	
	2022-01-01	2022-12-15	10	0.5055171	1.1304922
	2022-05-01	2022-12-15	10	1.9168187	0.9043248
	2022-10-01	2022-12-15	10	0.1723094	0.3074703
	2022-12-01	2022-12-15	10	0.1236108	2.0592164

Where Figure 9, shows the 8 years data of Meta stock price in a graph and its difference between ARIMA prediction vs LSTM prediction and real price this shows the values deviation in a graph. In figure 10, shows the Meta stock data of same 8 years data MSE values deviation in graph.

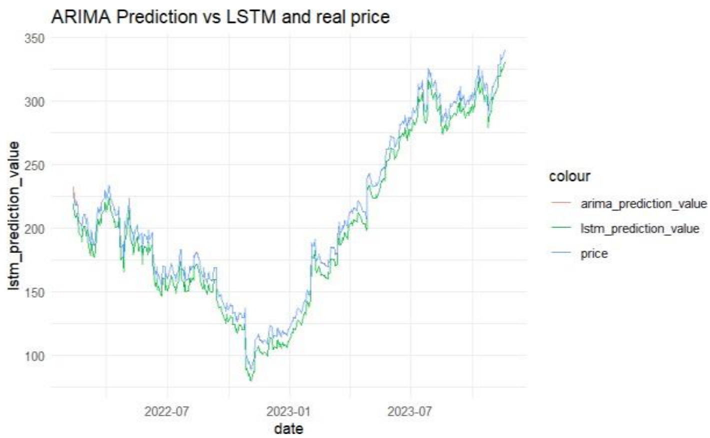

Figure 9. Meta 8 years data of LSTM vs ARIMA vs Real price

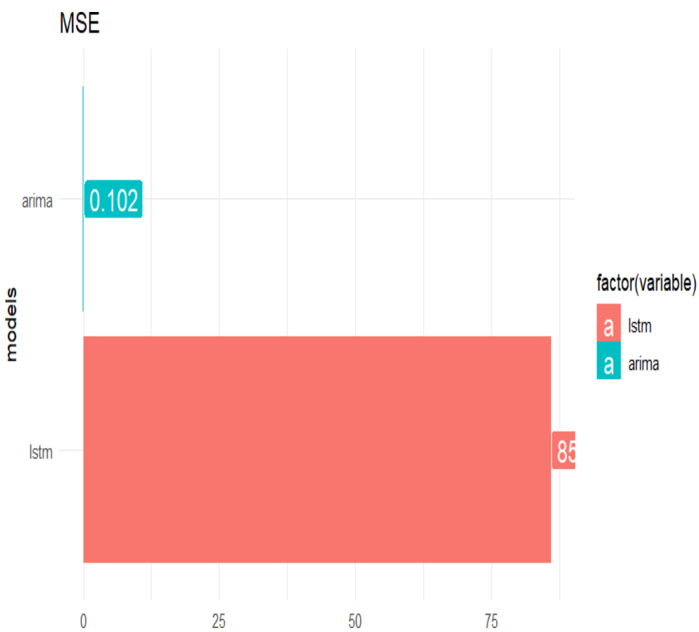

Figure 10. Meta 8 years data MSE value of LSTM vs ARIMA.

Here Figure 11, shows the 51 days of Meta stock price in a graph and its difference between ARIMA prediction vs LSTM prediction and real price this shows the values deviation in a graph. In figure 12, shows the Meta stock data of same 51 days data MSE values deviation in graph.

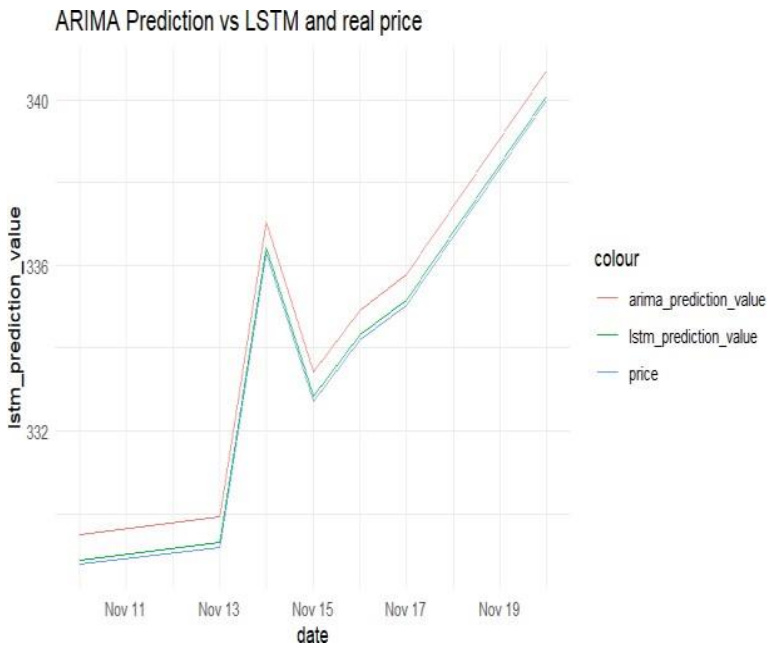

Figure 11. Meta 51 days data of LSTM vs ARIMA vs Real price.

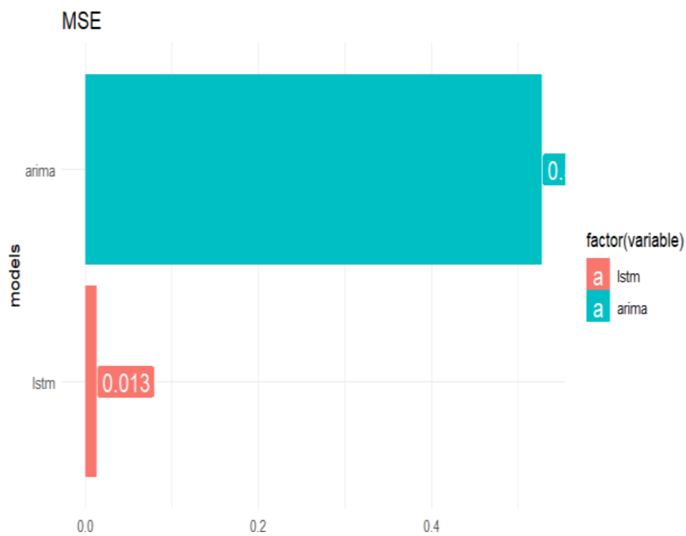

Figure 12. Meta 51days data MSE value of LSTM vs ARIMA

Table.4 Comparative analysis of Sun Pharmaceuticals stocks with LSTM and ARIMA based on MSE values has the stock name, start date from the year 2015 and end year 2022, then the different number of LSTM execution and MSE of LSTM and MSE of ARIMA. That shows the long periods have the MSE value on LSTM is high when it is compared with the ARIMA.

Table.4. Comparative analysis of Sun Pharmaceuticals stocks with LSTM and ARIMA based on MSE values

StockName	Startdate	Today	LSTM Executio ns	MSE of LSTM	MSE of ARMA
SUNPH ARMA. NS	2015-01-01	2022-12-16	10	21.781164414	0.006122811
			25	20.895835507	
			50	19.477460833	
	2016-01-01	2022-12-16	10	2.542603674	0.006571268
			25	2.662680688	
			50	2.858012297	
	2017-01-01	2022-12-16	10	42.08580959	0.02532591
			25	41.34476308	
			50	40.00324346	
	2018-01-01	2022-12-16	10	3.97440962	0.04453911
			25	3.82722243	
			50	3.57288388	
	2019-01-01	2022-12-16	10	16.4118324	0.2377968
			25	15.9120704	
			50	15.1506098	
	2020-01-01	2022-12-16	10	37.1441606	0.5893896
			25	37.1303989	
			50	37.0808802	
	2021-01-01	2022-12-16	10	24.9283194	0.4675936
			25	24.8106617	
			50	24.5829227	
	2022-01-01	2022-12-16	10	22.5267104	0.3902927
	2022-05-01	2022-12-16	10	31.822083	1.197612
	2022-10-01	2022-12-16	10	3.898514	1.645162
	2022-12-01	2022-12-16	10	54.03535	155.00280

Where Figure 13, shows the 8 years data of Sun Pharmaceuticals stock price in a graph and its difference between ARIMA prediction vs LSTM prediction and real price this shows the values deviation in a graph. In figure 14, shows the Sun Pharmaceuticals stock data of same 8 years data MSE values deviation in graph.

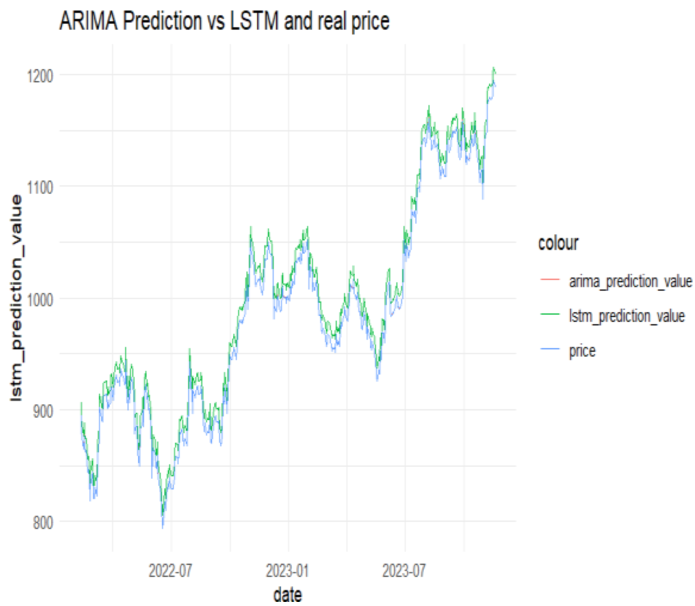

Figure 13. Sun Pharmaceuticals 8 years data of LSTM vs ARIMA vs Real price.

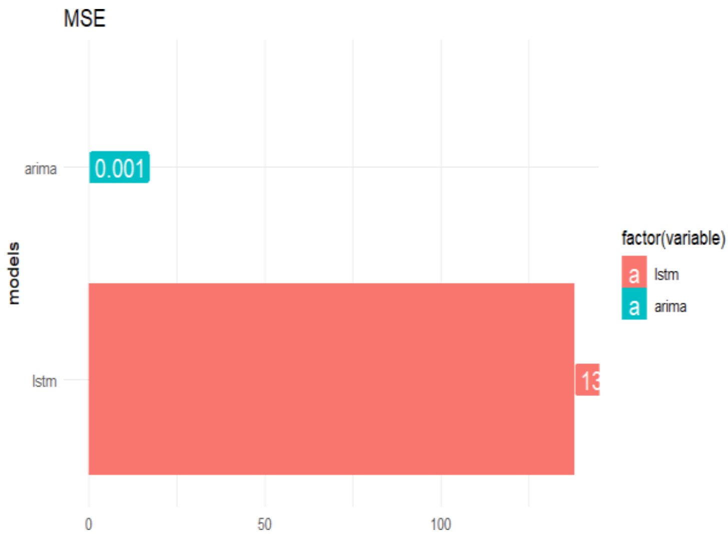

Figure 14. Sun Pharmaceuticals 8 years data MSE value of LSTM vs ARIMA.

Here Figure 15, shows the 51 days of Sun Pharmaceuticals stock price in a graph and its difference between ARIMA prediction vs LSTM prediction and real price this shows the values deviation in a graph. In figure 16, shows the Sun Pharmaceuticals stock data of same 51 days data MSE values deviation in graph.

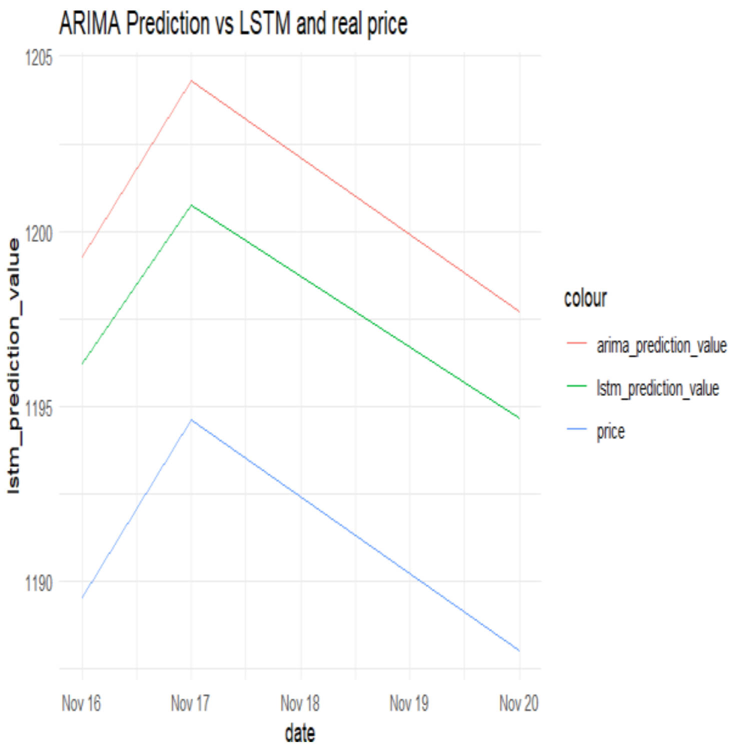

Figure 15. Sun Pharmaceuticals 51 days data of LSTM vs ARIMA vs Real price.

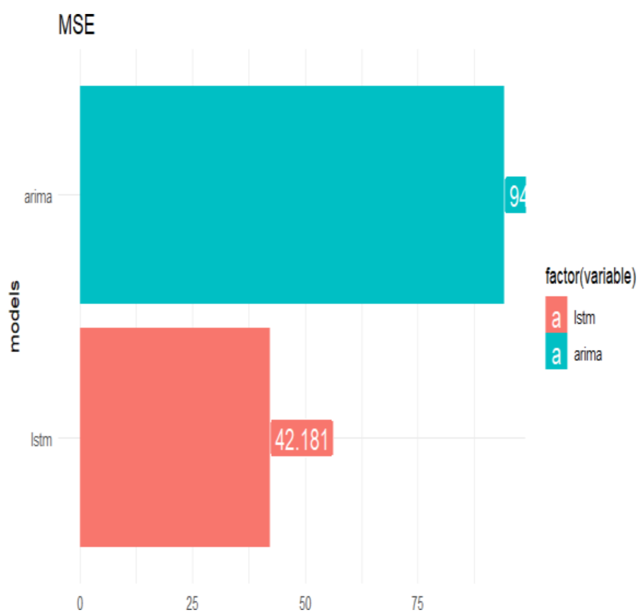

Figure 16. Sun Pharmaceuticals 51days data MSE value of LSTM vs ARIMA.

Table.5 Comparative analysis of KM Sugars stocks with LSTM and ARIMA based on MSE values has the stock name, start date from the year 2015 and end year 2022, then the different number of LSTM execution and MSE of LSTM and MSE of ARIMA. That shows the long periods have the MSE value on LSTM is high when it is compared with the ARIMA.

Table.5. Comparative analysis of KM Sugars stocks with LSTM and ARIMA based on MSE values

StockName	Start date	Today	LSTM Executions	MSE of LSTM	MSE of ARMA
KMSUGAR.NS	2015-01-01	2022-12-16	10	0.0726492819	0.0006367762
			25	0.0807609737	
			50	0.0942065098	
	2016-01-01	2022-12-16	10	0.2013670800	0.0003301258
			25	0.2106625282	
			50	0.2246525154	
	2017-01-01	2022-12-16	10	0.0638534739	0.0003816855
			25	0.0612296579	
			50	0.0570485815	
	2018-01-01	2022-12-16	10	0.0012890862	0.0000330519
			25	0.0014319433	
			50	0.0016684632	
	2019-01-01	2022-12-16	10	0.104883832	0.000679967
			25	0.107133519	
			50	0.110958857	
	2020-01-01	2022-12-16	10	0.637041366	0.002181621
			25	0.630379104	
			50	0.619258714	
	2021-01-01	2022-12-16	10	0.030504893	0.001866848
			25	0.030263318	
			50	0.028734082	
	2022-01-01	2022-12-16	10	0.0294462927	0.0009192511
	2022-05-01	2022-12-16	10	0.006776034	0.015625000
	2022-10-01	2022-12-16	10	7.029765e-03	1.643590e-06
	2022-12-01	2022-12-16	10	0.09143593	0.08999970

Where Figure 17, shows the 8 years data of KM Sugars stock price in a graph and its difference between ARIMA prediction vs LSTM prediction and real price this shows the values deviation in a graph. In figure 18, shows the KM Sugars stock data of same 8 years data MSE values deviation in graph.

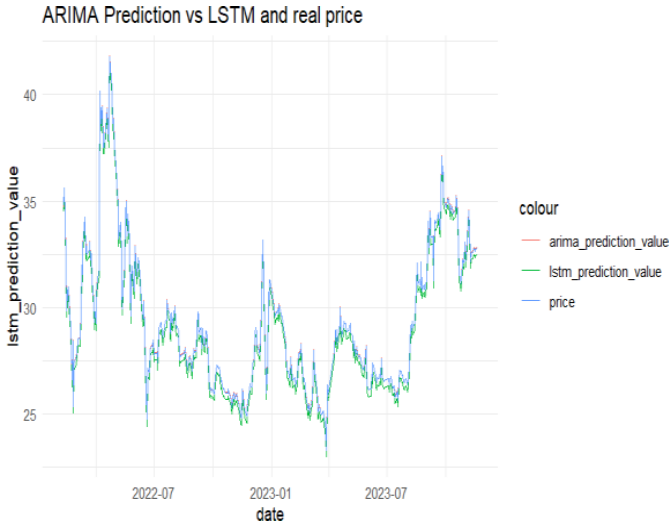

Figure 17. KM Sugars 8 years data of LSTM vs ARIMA vs Real price.

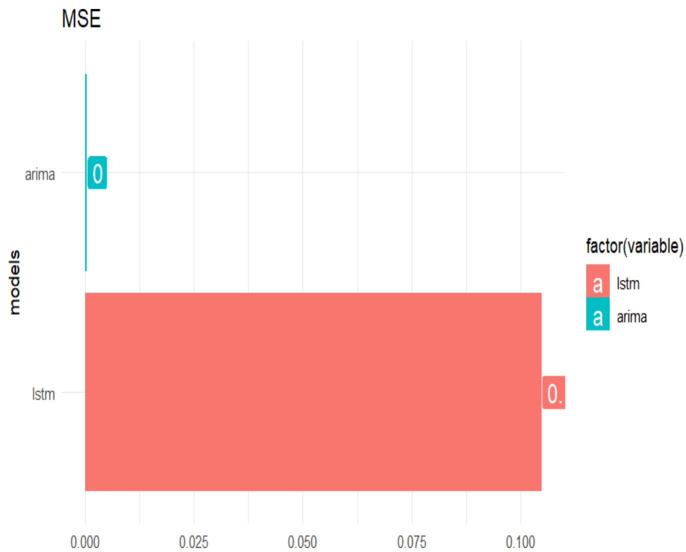

Figure 18. KM Sugars 8 years data MSE value of LSTM vs ARIMA.

Here Figure 19, shows the 51 days of KM Sugars stock price in a graph and its difference between ARIMA prediction vs LSTM prediction and real price this shows the values deviation in a graph. In figure 20, shows the KM Sugars stock data of same 21 days data MSE values deviation in graph.

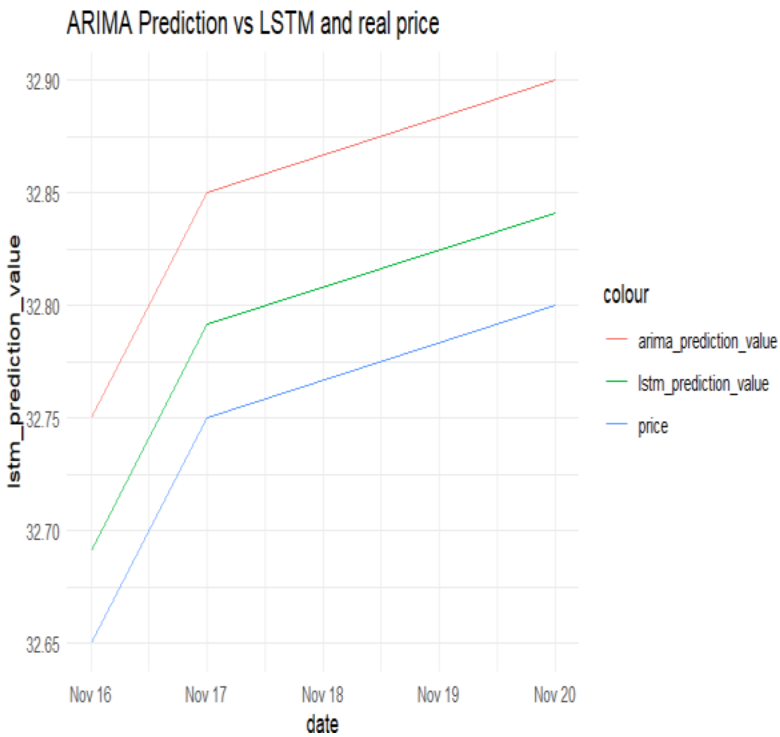

Figure 19. KM Sugars 21 days data of LSTM vs ARIMA vs Real price.

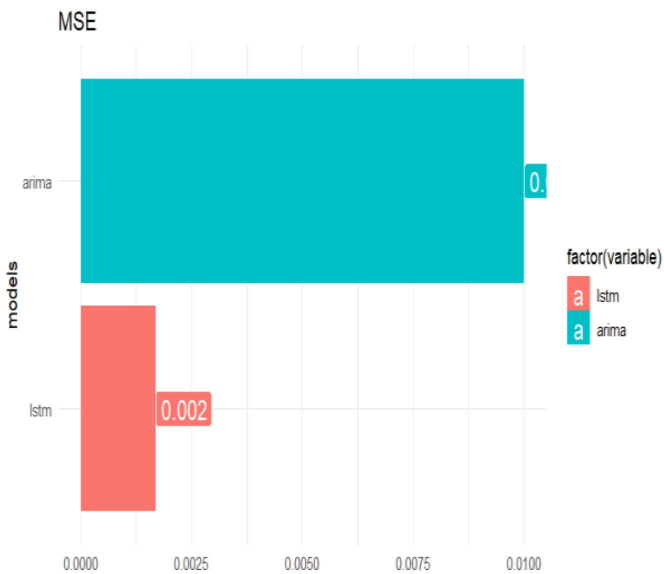

Figure 20. KM Sugars 21days data MSE value of LSTM vs ARIMA.

5. Conclusion and Future work

Comparative analysis of Table1, shows that Tcs(TCS) data of 8 year period of time LSTM having high MSE value compered to ARIMA and the company which has short period of time means ARIMA having the high MSE value. Table2, shows that Tesla (TSLA) data of 8 year period of time LSTM having high MSE value compered to ARIMA and the company which has short period of time means ARIMA having the high MSE value. Table3, shows that Meta(META) data of 8 year period of time LSTM having high MSE value compered to ARIMA and the company which has short period of time means ARIMA having the high MSE value. Table4, shows that Sun Pharmaceuticals (SUNPHARMA.NS) data of 8 year period of time LSTM having high MSE value compered to ARIMA and the company which has short period of time means ARIMA having the high MSE value. Table5, shows that KM Sugars(KMSUGARS.NS) data of 8 year period of time LSTM having high MSE value compered to ARIMA and the company which has short period of time means ARIMA having the high MSE value.

It is observed that both are providing good results but according to the time frame, the results gets vary. The LSTM produces a good result when it is used for daily forecasting model also the number of executions produces variation in the result. Though, increases in number of executions results in high time complexity. ARIMA produces good results when the forecast is done on a yearly or monthly basis and execution time is also less when it is compared with LSTM, which are shown in the analysis tables. According to our application/time frame, an experimental result shows that, comparatively, ARIMA is performing better than LSTM. ARIMA provides the least error values with good results in a short time.

Increased number of executions results LSTM to achieve the good results for long term investments. But, increasing the execution can makes the execution time higher that could be overcome by the parallel processing works in distributed mechanism reduces the execution time and provide better results.

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Conflicts of Interest

The authors have no conflicts of interest to declare.

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