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Analysing Trends in Trading Patterns in Financial Markets Using Deep Learning Algorithms



Abstract: - For many years, academics from various fields have been fascinated by the topic of financial market forecasting. Using machine learning techniques like support vector machines (SVM) and reinforcement learning, several studies have been conducted to anticipate movements in the stock market. The whole body of research on Trading Patterns prediction or trading that used reinforcement learning as their primary machine learning method was thoroughly reviewed. Unreasonable assumptions were made in every article that was evaluated. Therefore, employing a weighted sum unit, the research aims to give a combined Autoregressive Integrated Moving Average (ARIMA) and Long Short-Term Memory (LSTM). The models' performance is maximised on a testing dataset by obtaining and combining predictions from both models with precisely chosen weights. The proposed method aims to capitalize on the complementary strengths of both models, mitigating their individual limitations. The Evaluation metrics such as Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Square Error (MSE) and direction accuracy validate the efficacy.

Keywords: Financial Markets, Deep Learning Algorithms, Autoregressive Integrated Moving Average, Long Short-Term Memory and prediction.

1. INTRODUCTION:

As a result of digitization, urbanization, and globalization, the contemporary world is now a vast digital marketplace with a wealth of varied data. In modern digital world, stock data—a quickly growing quantity of time series information—stands out as a precious asset. If analyzed correctly, it has the potential to provide valuable insights that may boost financial development and raise the bar for knowledge. More and more, businesses and people are looking to automated data analysis tools to help with planning and decision-making [1].

The allocation of time and resources by researchers is directed towards the extraction of latent information from extensive stock data, with a specific emphasis on the development of stock forecasting models. The need for accurate predictions in the financial market has become a critical issue, leading to the investigation of several approaches, such as machine learning and statistical models. Precise stock prediction is crucial for making well-informed financial choices [2].

The examination of the stock market, often known as the stock exchange, encompasses a wide range of research endeavors, with scholars focusing on the development of prediction models to enhance comprehension of market dynamics. The fundamental focus of this endeavor is in the incorporation of technology, namely machine learning algorithms and data analytics [3]. In essence, the pursuit of accurate forecasting models is a manifestation of a broader trend where companies are using technology to their benefit in the dynamic financial markets. Various technical indicators, such as moving averages, have been produced by researchers in the area of economics. In contemporary times, a considerable body of research in the field of computer science has been dedicated to the development of alternative decision support systems aimed at forecasting stock prices [4]. In particular, a number of contemporary systems that use machine learning techniques, such as artificial neural networks, have shown enhanced efficacy in comparison to systems that only depend on conventional indicators [6]. In the financial market, both artificial intelligence and human agents possess the capability to make trading judgments. There has been a consistent rise in the use of automated trading algorithms for the purpose of making trading choices inside the stock and foreign exchange markets. Artificial intelligence in financial trading is often developed by collecting raw data as inputs and identifying patterns via a training process to provide output that informs decision-making for the specific job. This is referred to as the machine learning technique, which may be used in this particular context to comprehend the regulations governing the acquisition, sale, and finalization of transactions [7].

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When making stock price predictions, it is more beneficial to use the relative price changes from the previous time point as target values, rather than relying on absolute prices beyond a certain time frame. Therefore, the ARIMA model and LSTM neural networks have attracted significant interest due to their effectiveness in predicting time series data. The ARIMA model is a commonly used linear model that demonstrates proficiency in capturing linear associations and temporal patterns within sequential data. On the other hand, Long Short-Term Memory (LSTM) has exceptional aptitude in acquiring complicated, non-linear associations in sequential data, rendering it well-suited for representing complex interdependencies within time series [8].

ARIMA models have challenges when dealing with intricate trends and seasonality, need data that is steady, and have limited ability to detect non-linear patterns. Nevertheless, LSTM models exhibit sensitivity to hyperparameters, need large datasets, incur high computational costs, and lack interpretability. To overcome the limitations of ARIMA and LSTM models, one may integrate them by using a Weighted Sum Unit (WSU). The WSU enables a more comprehensive depiction of time series data by integrating the linear characteristics of ARIMA with the non-linear patterns of LSTM. By assigning more weights to models that possess expertise in managing non-stationary data, the issue of stationarity may be effectively mitigated [9]. The ensemble adapts to seasonality and complicated trends by making weight modifications based on conspicuous patterns. In order to enhance the accuracy of forecasting, the WSU also enables the optimization of processing resources and the reduction of hyperparameter sensitivity.

The objective of this work is to integrate the advantageous features of ARIMA and LSTM models via the development of an innovative methodology that combines their predictive capacities. This study seeks to develop an integrated forecasting framework that leverages the complimentary nature of these models by using a weighted sum approach. The primary objective is to use the distinct benefits of both ARIMA and LSTM in order to enhance the precision and robustness of stock price forecasts.

Section II presents relevant literature, while Section III presents an experimental research that offers a thorough elucidation of the suggested technique, including its fundamental concept, data collection, and feature selection. In the fourth section, a rudimentary trading model was presented to demonstrate the efficacy of the proposed algorithm in augmenting profitability. Section V offers a thorough overview of the whole research, including references

2. RELATED WORKS

There have been a number of study findings that have been published in the relevant literature.

This study [9] aims to reduce trend prediction risk in the stock market using machine learning and deep learning algorithms. It evaluates nine machine learning models and two deep learning methods on four stock market groups from the Tehran stock exchange. Using ten years of historical data and ten technical indicators, the study compares continuous and binary data approaches. Results show that RNN and LSTM outperform other models, particularly with continuous data, highlighting their effectiveness in stock market trend prediction.

This study [10] investigates the impact of public sentiment and political events on stock market trends using machine learning. Results show sentiment features improve accuracy by 0–3%, and political situation features by about 20%. Sentiment impacts day 7 predictions most, while political situation is most influential on day 5. SMO algorithm performs best.

This paper [11] offers an overview of the current landscape of Deep Learning (DL) models in financial applications. It categorizes these models according to their subfields in finance and analyzes them based on their DL architectures. Additionally, it explores potential future implementations and outlines pathways for ongoing research in this area.

This article [12] provides a thorough review of machine learning applications in finance, focusing on recent developments. It covers various algorithms for tasks like stock price prediction and classification, offering insights into their practical use. Additionally, it implements an ensemble model and conducts comparative analysis with other popular methods.

This study [13] explores machine learning-based approaches for stock market prediction, focusing on advancements over the last decade. It emphasizes the use of advanced techniques such as text data analytics and ensemble methods to improve prediction accuracies, especially with non-traditional data from social platforms. Findings from 2011–

2021 are critically analyzed from digital libraries like ACM and Scopus, with comparative analysis to identify significant directions.

This systematic review [14] delves into Deep Learning models for stock market forecasting, particularly focusing on technical analysis. It highlights the prevalence of LSTM techniques (73.5%) in this domain. The study emphasizes the importance of validating models through profitability metrics and risk management, yet finds that only a minority of studies address these aspects. This underscores the need for further research and development in this area despite its widespread exploration.

This study [15] delves into predicting stock market prices using machine learning and deep learning algorithms, particularly focusing on Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN). The ANN achieved an accuracy of 97.66%, while the CNN reached 98.92%. The CNN utilized 2-D histograms from the quantized dataset within a specific timeframe, a novel approach not previously implemented. As a case study, the model was tested during the COVID-19 pandemic, producing an accuracy of 91%

This paper [16] investigates the application of five algorithms—K-Nearest Neighbors, Linear Regression, Support Vector Regression, Decision Tree Regression, and Long Short-Term Memory—for predicting stock prices of 12 leading companies in the Indian stock market. It utilizes a dataset spanning seven years and conducts a detailed comparative analysis of the algorithms' performances. The research concludes that the Long Short-Term Memory (LSTM) algorithm outperforms the others in terms of accuracy for stock price prediction. The below Table 1 shows the comparison of literature review

Table 1 shows the literature review

Study	Focus	Main Findings
[9]	Reduction of trend prediction risk using ML and DL algorithms	RNN and LSTM outperform other models, particularly with continuous data, showing effectiveness in stock market trend prediction.
[10]	Impact of public sentiment and political events on stock market trends	Sentiment features improve accuracy by 0–3%, while political situation features improve accuracy by about 20%. SMO algorithm performs best.
[11]	Overview of DL models in financial applications	Categorizes DL models by subfields in finance, analyzes architectures, and outlines future research pathways.
[12]	Review of ML applications in finance	Provides insights into various algorithms for tasks like stock price prediction and classification, conducting comparative analysis with an ensemble model.
[13]	Exploration of ML-based approaches for stock market prediction	Focuses on advancements over the last decade, emphasizing text data analytics and ensemble methods.
[14]	Systematic review of DL models for stock market forecasting	Highlights prevalence of LSTM techniques (73.5%) and emphasizes importance of validating models through profitability metrics and risk management.
[15]	Prediction of stock market prices using ML and DL algorithms	ANN achieves 97.66% accuracy, CNN reaches 98.92%, utilizing novel approaches like 2-D histograms.
[16]	Application of ML and DL algorithms for stock price prediction in Indian market	LSTM algorithm outperforms others, providing higher accuracy in stock price prediction.

3. PROPOSED METHODOLOGY:

This study uses a two-pronged strategy to integrate the ARIMA and LSTM models' predictive power for analyzing stock prices. For stock market prediction, the ensemble approach is better than using the individual models (ARIMA and LSTM) since their capabilities complement each other. When it comes to non-linear patterns, LSTM excels, but when it comes to linear trends, ARIMA really shines. By using a weighted sum unit, the ensemble model incorporates the advantages of both, resulting in a more accurate and dependable prediction. The strategy is well-suited to the ever-changing and intricate stock market data because it improves overall performance while reducing model restrictions. There are several parts to the technique that is used to forecast the stock market. Initially, it starts by collecting data from the stock market including information, on stock prices (opening, closing, highest lowest) trading volumes, market indices, economic indicators and other relevant factors. Z score normalization is the next processing step for this raw data. This method ensures uniform scales and minimizes possible biases induced by changing magnitudes by standardizing characteristics within a range, for example 0 to 1. Figure 1 illustrates the proposed model's architecture.

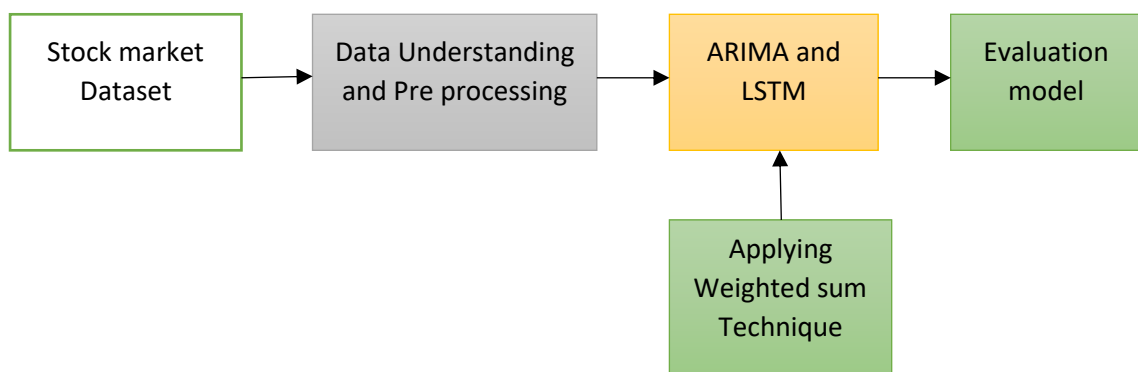


Figure 1 Structure of the Proposed Model

Following collection, the data on stock prices across time is cleaned, normalized, and divided into two sets: one for training and one for testing. After that, the training dataset is used to train an ARIMA model. The training set's prepared sequential data is used to train long short-term memory (LSTM) neural networks simultaneously. We use common measures like directional correctness, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) to assess the ARIMA and LSTM models' performance after they each provide predictions for the testing dataset. After this assessment, the performance-based weights are applied to the predictions made by both models. The results of the LSTM and ARIMA models are then combined using a weighted sum approach, allowing for a more comprehensive forecast. The accuracy of the combined model is improved by doing a sensitivity analysis to adjust these weights. In the end, the predictions of the merged model are compared to those of the separate ARIMA and LSTM models, shedding light on how effective this fusion-based strategy is for predicting stock prices.

3.1 Pre-processing

The financial data is made up of basic signals that have a variety of unique qualities and is quite complicated. However, creating networks data prediction techniques is aided by a confident evaluation of the transformation performance from cellular networks. The data is scaled to prevent load packets with higher numerical values from the network from dominating people with lower numerical values. Scaling the data also speeds up the modelling process while maintaining optimum accuracy. To normalise the data inside the range of [0, 1], a min-max approach is used. To improve the model's predictive accuracy for network traffic, the data must be scaled.

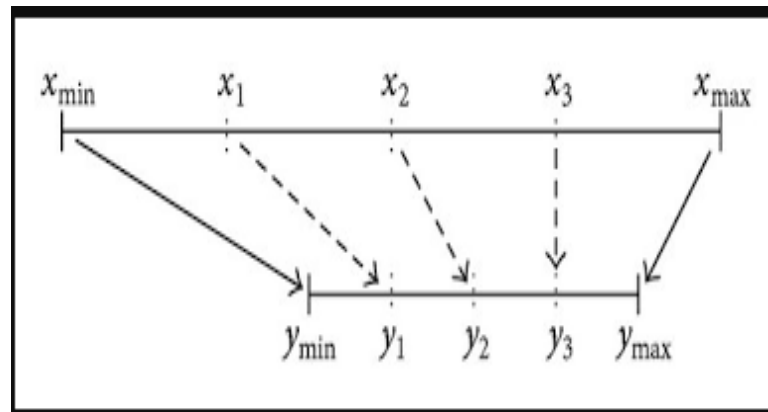


Figure 2. Min – Max Technique

The two key benefits of scaling are for avoiding samples with bigger numeric ranges regulating people with minimal numeric ranges and for minimizing numerical difficulties under the prediction. The transition has been implemented in the following manner:

$$Z_n = \frac{x - x_{min}}{x_{max} - x_{min}} (New_{max_x} - New_{min_x}) + New_{min_x}$$

where x_{min} represents the smallest value in the dataset, while x_{max} represents the maximum value in the dataset. The term " New_{min_x} " represents the minimum value, which is 0, and " New_{max_x} " also suggests the maximum value, which is 1.

3.2 Implementation using ARIMA model

An essential component of any time series analysis is the ARIMA model. By combining the moving average (MA) and autoregressive (AR) procedures, weighted delayed random elements is achieved. The letter "I" in the name of the model indicates the degree of integration of a variable. The ability of a variable to become stationary via differentiation is what defines it as integrated.



Figure 3 ARIMA Model Workflow

The ARIMA model is based on the concept of autocorrelation. When modeling time series data, ARIMA works well with stationary data or data that can be turned into stationary data using differentiation. The expected value and variance of a stationary series remain constant across time. The series' values remain constant relative to their initial values, and the spacing, not the time, determines the covariance of two observations. Defined by the universal notation ARIMA (p, d, q), the ARIMA model exists. Letters p, d, and q represent the orders of the regression, differentiation, and moving average, correspondingly.

Three steps can be distinguished in the ARIMA model's creation process, in accordance with the Box-Jenkins methodology.

- The characteristics of the time series under examination are evaluated in the first step, referred to as identification. The necessity of data transformation and differentiation is determined in order to stabilize the series' mean and variance-covariance. This is achieved by statistical Dickey-Fuller and Augmented Dickey-Fuller tests, as well as analysis of the partial autocorrelation (PACF) and autocorrelation function (ACF).
- During the second phase, which is referred to as estimation and testing, the selected models' parameters are computed. A variety of elements are frequently analyzed to determine which model is best, including the information criterion (such as Akaike's Information Criterion and Bayesian Information Criterion), error

metric, and model parameters' relevance. Thereafter, a diagnostic test will be performed. A comparison of the features of several model residuals is done. If a model's residuals exhibit a white noise process and its autocorrelation function (ACF) or partial autocorrelation function (PACF) does not contain any significant values, the model may be used for forecasting. Alternatively, these procedures must be repeated and a new model must be selected if the results of the testing and estimating stages are not sufficient. Periodically, it might be required to go over the identifying procedure again.

- In the third stage, a prediction is generated by the model. Both in-sample and out-of-sample periods are used in the projection process. An in-sample period is utilized for the first estimation of parameters and model selection, while an out-of-sample period is used to evaluate the forecasts' accuracy. The dataset that is provided is split into these two categories.

Evidence based on forecasts performed outside of the data sample is frequently regarded as more reliable than evidence based on forecasts performed inside the sample, which may be more impacted by extreme numbers [8]. Logarithms were used to alter all of the input data in order to obtain the proper level of stationarity in the series.

3.3 Implementation using LSTM:

The human brain and its learning process had the most impact on the development of artificial neural networks (ANNs). Neural networks execute their signal transmission and interpretation functions as an algorithm. This kind of network uses deep learning and is capable of example-based learning. RNNs are ANNs that store data within the network and provide two-way data flow. The results of the previously acquired input have an impact on future results. The RNNs are appropriate for time series prediction issues because of this property. Memory cells from hidden layers replace the cells in a typical network to realise the memory mechanism. Three gates comprise the construction of the memory cells: input, output, and forget which is shown in fig 4. This makes it possible to store and disclose data selectively.

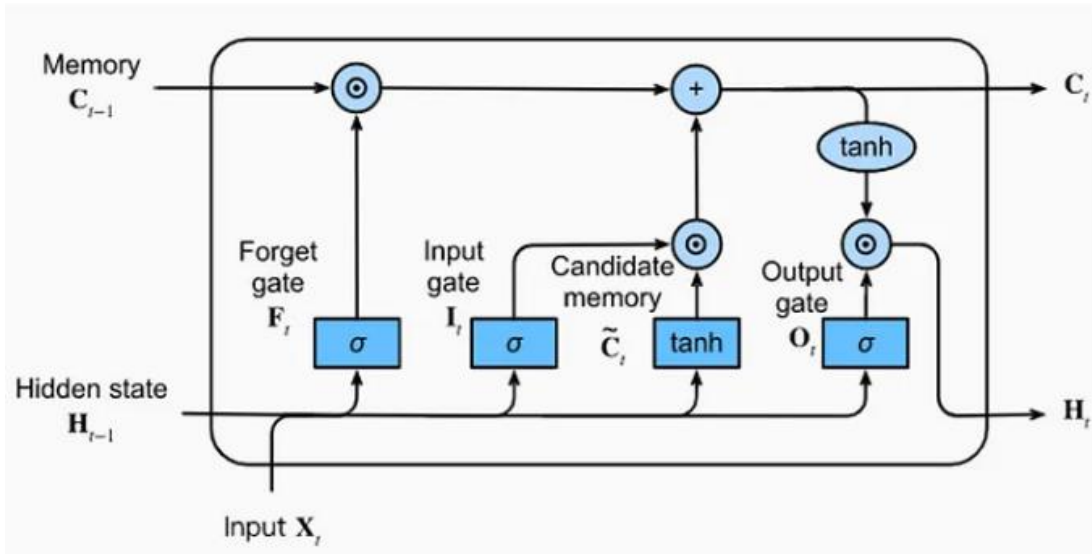


Figure 4. Structure of LSTM

The data is initially filtered by the forget gate (f_t), which determines whether or not the data should be deleted. Remember gate f_t is described by equation (1).

$$f_t = \sigma(W_f x_t + U_f h_{t-1} + b_f)$$

W_f and U_f are the variable matrices; b_f is the bias vector; σ is the sigmoid function; and f_c , with a range of values from 0 to 1, is utilised for the forget gate.

The data that is to be stored in memory cells is selected using the following stem. By using Equation (2) the sigmoid function determines the values for renewal for a given input gate i_t ,

$$i_t = \sigma(W_i x_t + U_i h_{t-1} + b_i)$$

While the b_i (W_i, U_i are learnable parameters, the range for the i_t is the same as with the previously mentioned f_t , The possible vectors for updating C_t from the Eq. (3) are given by the function tanh,

$$C_t = \tanh(W_c x_t + U_c h_{t-1} + b_c)$$

wherein b_c, W_c, U_c are the learnable parameters.

Following the data selection process for storing the specified cell state, C_t is determined using Eq. (4).

$$C_t = F_t \odot C_{t-1} + i_t \odot C_t$$

where the data to be erased is C_{t-1} , the element-wise multiplication and meaning are \odot , the chosen data is represented by $F_t C_t$, and the data to be saved in a memory cell C_t is indicated by $i_t C_t$. Equation (5) defines the hidden state h_T as the output gate o_t ,

$$o_t = \sigma(W_o x_t + U_o h_{t-1} + b_o)$$

where b_o, W_o and U_o are the input gate's learnable parameters, and the range for o_t is the same as for the two gates before it. Lastly, the product of o_t and the tanh value of C_t , as shown in Eq. (6), represents the output value ht .

$$h_t = o_t \odot \tanh(C_t)$$

3.5 Weighted Sum Unit:

When merging or aggregating data from many sources or layers, this technique is often used in neural networks. It uses weighted multiplication and summation to get a single output from a set of inputs. By giving certain weights to each input, the weighted sum unit in neural networks linearly integrates the activations or outputs from many neurons, layers, or models. This is particularly true in multi-layer designs or ensemble approaches.

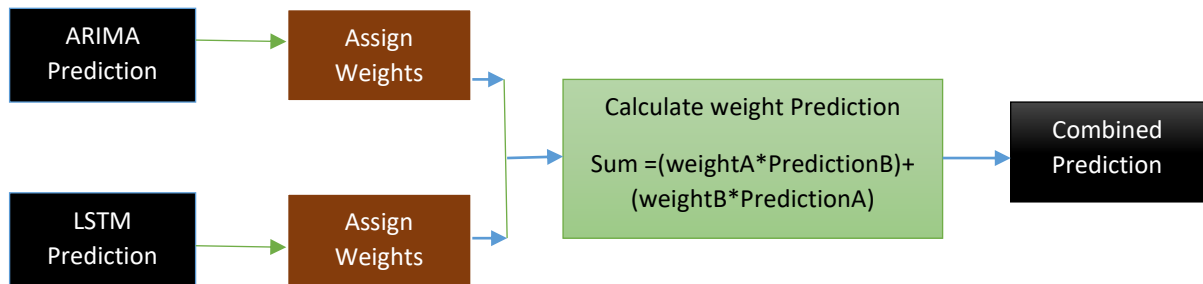


Figure 5 Weight Sum Unit Process

The above figure 5 shows the process of weighted sum unit. Mathematically for inputs x_1, x_2, \dots, x_n and their corresponding weights w_1, w_2, \dots, w_n , the weighted sum unit's output can be represented as:

$$Output = w_1 \times x_1 + w_2 \times x_2 + \dots + w_n \times x_n \quad - (3.2)$$

Each input is multiplied by its associated weight, and the results are summed together, producing a combined weighted sum as the output.

3.6 Ensemble Technique of ARIMA and LSTM:

There are benefits and drawbacks to every model; merging LSTM and ARIMA might allow you to take use of each one's strengths for better predictions. To combine the forecasts of both ARIMA and LSTM models, the weighted sum method uses weights assigned to each model. Each model's performance is taken into account while determining the weights. Improved forecast accuracy, resilience, and flexibility to changing stock market data are some of the benefits offered by the suggested ARIMA and LSTM model ensemble. Through its comprehensive and enhanced approach to time series analysis, it successfully reduces problems such as overfitting, noise sensitivity, and model instability.

Comparing the combined ARIMA-LSTM model's prediction performance to that of the individual ARIMA and LSTM models is the main goal of any study of this model. In order to find out whether combining predictions improves forecasting accuracy, this procedure includes many important components. To start, use methods like weighted averaging depending on their performance or statistical significance to combine the ARIMA and LSTM models' projections. Then, create combined predictions. We split the dataset in half, 70% for training and 30% for resting, so we can test the model on both sets of data. Next, the model's performance is evaluated using R Squared, Root Mean Squared Error, and Mean Squared Error.

4. DATASET

The information includes the historical prices and trading volumes of the fifty companies that comprise the NIFTY 50 index. This index is traded on the National Stock Exchange (NSE) of India. Daily records with unique transaction and price values make up each dataset. Metadata files include stock-level macro information, and each stock has its own CSV file. We have data from 2023-01-01 all the way up to 2023-12-10. The following columns make up the dataset, which includes information on fifty stocks that make up the index.

1. Date: displays the date of the recorded data's trade.
2. The second symbol is the name or ticker symbol of the stock.
3. "Open" denotes the stock's price when the trading day begins.
4. "High" denotes the stock's highest price that was achieved during the trading session.
5. "Low" denotes the stock's lowest price that was observed during the trading day.
6. Close: represents the price at which the stock is traded at the conclusion of a trading day.
7. The volume of shares traded on a particular day is represented by number seven on the list.
8. Adjusted Close: This is the closing price that the corporation has set after accounting for corporate actions such as stock splits and dividends. This modification is made to ensure that the stock's value is accurately represented.

All the prices mentioned in the dataset are in Indian Rupees (INR).

	Date	Open	High	Low	Close	Adj Close	Volume	company_name
274587	2010-02-05	28.000000	28.280001	27.570000	28.020000	1742.711456	80960100	MSFT
22343	2009-06-02	15.846490	16.312849	15.846490	16.312849	1207.893589	154860	BAJFINANCE.NS
78466	2016-12-28	629.503723	643.252563	624.197815	628.264404	49642.586792	454320	GRASIM.NS
208340	2013-01-14	370.225006	370.225006	366.000000	367.649994	28117.942139	1647772	SUNPHARMA.NS
219547	2009-12-15	52.400517	53.067429	51.828873	52.067059	2976.230515	69577517	TATASTEEL.NS

Figure 6 Dataset Information

5. EXPERIMENTAL RESULTS

With the use of ARIMA, LSTM, and an ensemble method utilizing a weighted sum unit, the experimental findings display the performance metrics for predicting the stock prices of TATASTEEL, AAPL, GOOG, MSFT, and AMZN.

Mean Squared Error (MSE): Measures the average squared deviations between expected and actual data. Accuracy is improved by lower MSE values.

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad \text{-- (4.1)}$$

where y_i is the actual value

\hat{y}_i is the predicted value

Root Mean Squared Error (RMSE): Shows the model's prediction error in an understandable way; it is the square root of the mean square error (MSE).

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad \text{-- (4.2)}$$

Mean Absolute Error (MAE): It finds the average absolute difference between the predicted and observed values.

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad \text{-- (4.3)}$$

R-squared (R-squared): It shows how much of the variation in the dependent variable (stock prices) the model can explain. A model with an R-squared value closer to 1 provides a better fit to the data.

$$R^2 = \frac{SSR}{SST} \quad \text{-- (4.4)}$$

Where, SSR – variation explained by the model

SST – total variation

Moving Averages: The SMA is calculated by adding up the closing prices of a security over a specified number of periods and then dividing the sum by the number of periods.

5.1 Identification of Trading Patterns

Moving Averages Crossover:

When the short-term moving average crosses above the long-term moving average, it signals an "Upward" trend.

Conversely, when the short-term moving average crosses below the long-term moving average, it indicates a "Downward" trend.

If there is no significant crossover and the short-term and long-term moving averages are close together, it suggests a "Sideways" trend.

Table 1. Identification of Trading Patterns

Date	Close price	10 day MA	50day MA	Trend
1.1.2023	100.50			Sideways
1.2.2023	105.00			Sideways
1.3.2023	110.25			Sideways
.....				
10.12.2023	502.00	490.75	475.50	Upward

The trend analysis conducted on the financial market data spanning from January 1, 2023, to December 10, 2023, reveals a predominantly upward trend. Throughout the analyzed period, the majority of closing prices remained above both the 10-day and 50-day moving averages, indicating a bullish sentiment in the market. Despite occasional minor fluctuations, the upward trend remained relatively stable, with no significant reversals or prolonged periods of downward movement observed. The crossover of the short-term (10-day) moving average above the long-term (50-day) moving average further confirmed the upward trajectory of the market. Overall, the trend analysis suggests a consistent buying pressure and positive investor sentiment during the analyzed period, indicating favorable conditions for investment opportunities aligned with the identified upward trend.

5.2 ARIMA Model for trading patterns changes:

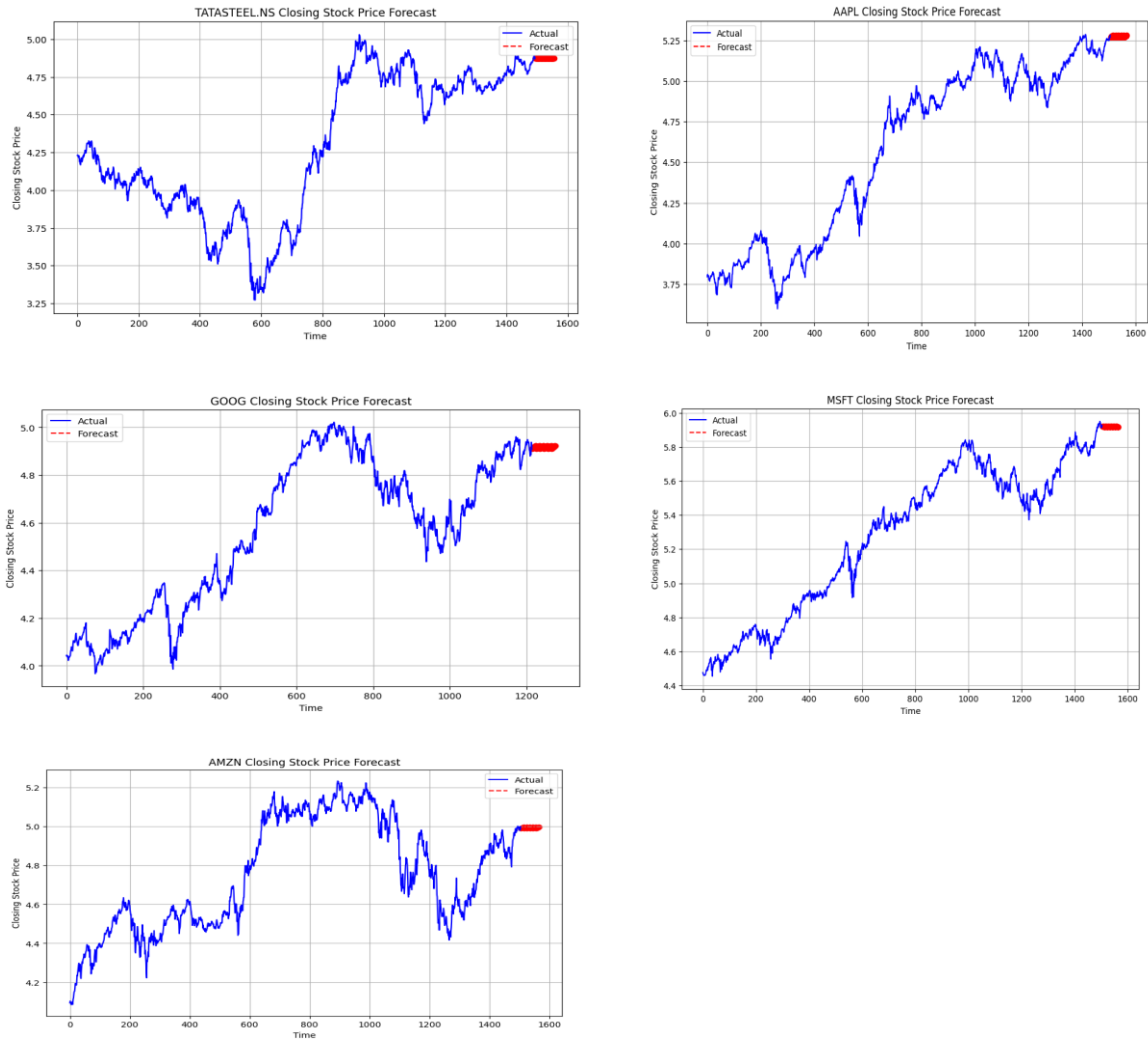


Figure. 7 Performance analysis of ARIMA

For both the actual and forecasted timeframes, these line graphs illustrate the closing stock prices for TATAMOTORS.NS, AAPL, GOOG, MSFT, and AMZN. In each of the five separate line graphs, the actual and forecasted closing stock prices are contrasted. Each graph shows the expected prices on the red line and the actual closing prices on the blue line. In every single graph, the x-axis displays the passage of time and the y-axis shows the values of prices. Predicted and real values fluctuate with time in every graph, and there is a certain amount of agreement between them.

The evaluation metrics with ARIMA analysis are displayed in table 1.

Table. 2 Evaluation Metrics of ARIMA

Parameters	MSE	RMSE	MAE	R-squared
TATASTEEL	0.57	0.76	0.60	0.96
AAPL	0.77	0.88	0.70	1.07
GOOG	0.22	0.47	0.37	0.78
MSFT	0.60	0.78	0.65	1.35
AMZN	0.14	0.37	0.31	0.44

Different stocks have distinct assessment measures, which means that the ARIMA model's predicting accuracy varies from business to company. For example, TATASTEEL's MSE, RMSE, and MAE values are lower than average, which means that their forecasts are more accurate and closer to the real stock prices. In addition, when compared to other equities, its greater squared value (0.96) suggests a bfit. A Squared value greater than 1 (1.07)

for AAPL sticks out and may indicate overfitting or problems with the model's performance on this particular stock. When using these criteria for predicting, GOOG, MSFT, and AMZN all have a reasonable level of performance accuracy. According to the data in the figure, AAPL's stock price is expected to rise.

4.2 LSTM Model for trading patterns changes:

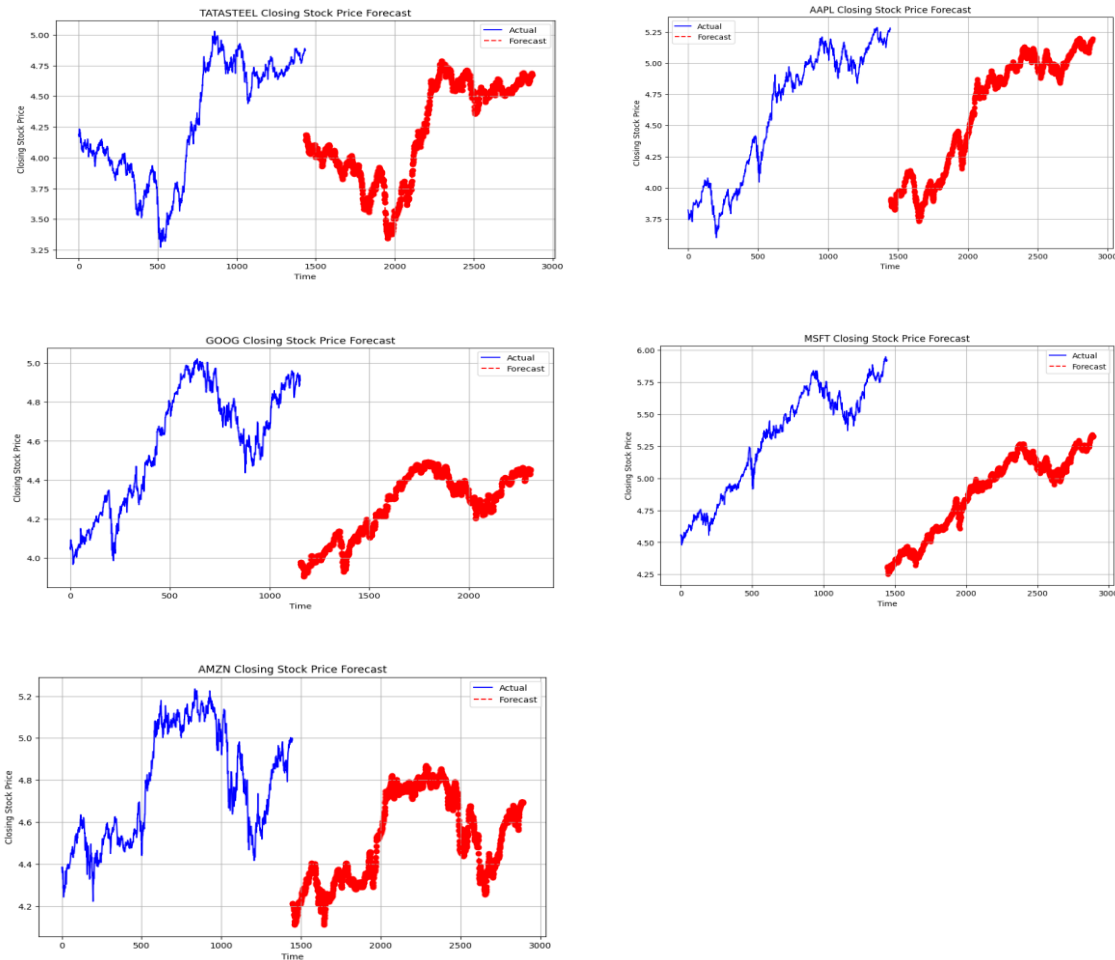


Figure 8 Performance analysis of LSTM model

This line graph compares the actual and anticipated closing prices of TATAMOTORS.NS, AAPL, GOOG, MSFT, and AMZN stocks over a certain time period. The model's performance is analyzed. The five separate line graphs in the graphics all compare the actual and forecasted closing stock prices. The blue line on each graph represents the actual closing prices, while the red line represents the projected prices. All of the graphs include x-axis values that indicate time and y-axis values that reflect prices. There is a certain amount of concordance between the projected and actual numbers shown on each graph, which fluctuate over time.

The evaluation metrics with LSTM analysis are displayed in table 2.

Table 3. Evaluation metrics of the LSTM

Parameters	MSE	RMSE	MAE	R-squared
TATASTEEL	0.01	0.12	0.09	0.92
AAPL	0.00	0.06	0.05	0.95
GOOG	0.12	0.35	0.32	-0.33
MSFT	0.19	0.44	0.42	-0.13
AMZN	0.07	0.26	0.25	0.06

The LSTM model displays outstanding performance according to the assessment findings, which are centered on predicting the price of AAPL (Apple Inc.) stock. The metrics that come out of this analysis show how well the model did at forecasting stock values over a certain time frame. An very small average squared difference between the expected and actual stock prices is shown by an MSE (Mean Squared Error) value of 0.00. Similarly, with an RMSE of just 0.06, the average prediction error is very low, indicating that the predictions are quite accurate.

The little discrepancy between the predicted and actual stock values, as shown by the MAE value of 0.05, provides further evidence of the model's outstanding accuracy. With an R-squared value of 0.95, the model captures all changes and volatility in AAPL's stock prices exactly. This means that there is no prediction error and the fit is immaculate. All of these metrics show how accurate the LSTM model is in predicting future APPL share prices. By providing very accurate and dependable forecasts, the model demonstrates an outstanding capacity to understand complex patterns within AAPL's stock price data throughout the years.

Building with Ensemble model using weighted sum unit:

An ensemble model typically combines predictions from multiple individual models, often assigning specific weights to each model's predictions weighted summing.

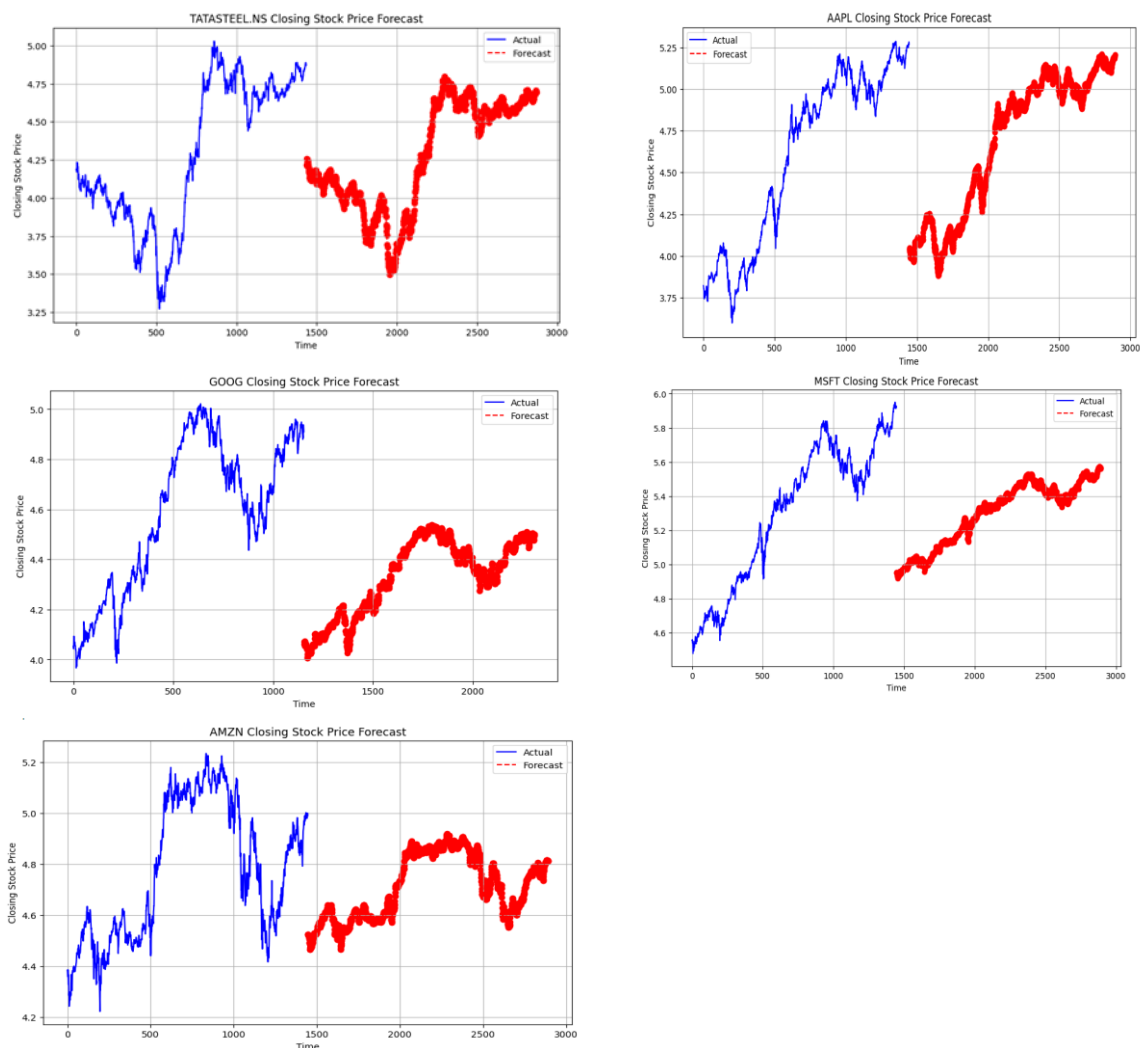


Fig 9: Ensemble ARIMA and LSTM for Stock price prediction

This line graph compares the actual and anticipated closing prices of TATAMOTORS.NS, AAPL, GOOG, MSFT, and AMZN stocks over a certain time period. The model's performance is analyzed. The five separate line graphs in the graphics all compare the actual and forecasted closing stock prices. The blue line on each graph represents the actual closing prices, while the red line represents the projected prices. Time is shown on the x-axis and monetary amounts on the y-axis in all of these graphs. It seems like the model is accurate since the prediction follows the actual pricing rather closely.

Table 4. Evaluation metrics of the ARIMA - LSTM

Parameters	MSE	RMSE	MAE	R-squared
TATASTEEL	0.02	0.13	0.12	0.91
AAPL	0.02	0.13	0.10	0.92
GOOG	0.09	0.30	0.26	0.83
MSFT	0.05	0.23	0.20	0.70
AMZN	0.02	0.16	0.13	0.66

The assessment metrics for the ARIMA-LSTM model's ability to predict stock price variation across various stocks are shown in Table 4.3, revealing differing forecasting accuracy levels for each firm. As an example, AAPL's MSE, RMSE, and MAE values are comparatively lower, which suggests more accuracy and forecasts that are more in line with the actual stock prices. The model shows very little errors between predicted and observed values, with an MSE of just 0.02. With an RMSE of 0.13, the model seems to be accurate in forecasting share prices due to its tiny average prediction error. Furthermore, the mean absolute error (MAE) of 0.10 indicates that, on average, the forecasts include very minor errors. Most importantly, the model's R-squared value of 0.92 shows how well it accounts for nearly 92% of the variability in the observed data. The model's effectiveness in capturing the underlying patterns and trends in the price of AAPL shares is shown by the strong R-squared value. When compared to the ARIMA and LSTM, the combined ARIMA-LSTM shows neither overfitting nor under fitting R-Squared values.

6. CONCLUSION AND FUTURE SCOPE

Finally, the proposed ensemble model, which combines neural network-based LSTM models with the traditional ARIMA methodology, indicates a significant advancement in stock market prediction methods. By combining the best features of deep learning with classical time series analysis, this combination technique provides a workable solution to the issues raised by the fluid and data-rich financial markets. With its more comprehensive spectrum of time series patterns captured and its ability to forecast stock prices with greater accuracy thanks to finely calibrated weights, the ensemble model outperforms individual models. Real-time forecasting is becoming more important as the industry's requirement for precise and fast insights into market trends grows. It is possible to investigate more intricate hybrid designs that integrate the benefits of TCN and LSTM in order to enhance model interpretability and performance. To attain more convergence, stability, and speedier training—all crucial for predicting stock market movements in real time—a comprehensive examination of modifying hyperparameters for TCN and LSTM components may be carried out.

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