Improvement in stock market trend and price prediction using Hybrid Deep Learning models.

Mr. Anupa Sekhar Dash*, Research Scholar,
Affiliation: MIT College of Management, MIT Art, Design & Technology University, Pune, India
Email id: anups.dash@gmail.com

Abstract

Identifying stock market trend and predicting the future price is challenging due to due to complex in nature of investments. Stock market trend is associated with investor behavior which depends on the underlying information of micro and macroeconomic data. We often see the stock prices influenced by the sentiment of investors on various macro-economic factors. In this paper we have tried to use sentiment analysis data along with previous prices and trend of 50 stocks from NIFTY 50 index to identify the future trend and future price of the stock. Using various deep learning model, we tried to predict the trend of stocks and next day close price of the Indian stocks The result suggests that the sentiment analysis score of macro-economic data has a strong influence on the trend prediction and the stock price prediction. Using deep learning model we have achieved the RMSE of 0.0259 for the predicted close price of 50 stocks. The accuracy of prediction of the stock prices through the LSTM deep learning models improves using the sentiment analysis score of both micro and macro-economic data. The finding will help investors in taking informed decisions.

Keywords—Stock Market, Sentiment Analysis, LSTM, Prediction, Deep Learning

Introduction

Forecasting stock market movements has consistently been a primary concern for researchers and investors because of the possible financial gains and the intrinsic difficulties associated with market volatility. Advanced computational approaches have led to the emergence of hybrid deep learning models as effective instruments for stock price forecasting through the integration of diverse data sources. This research focuses on applying these models to predict trends in the fifty top stocks, constituent of NIFTY 50 Index of Indian market utilizing historical price data alongside macroeconomic and microeconomic sentiment information.

The NIFTY 50 index reflects the performance of 50 prominent companies listed on the National Stock Exchange of India, acting as a benchmark for the Indian equities market. As of September 30, 2024, the Nifty 50 Index accounts for approximately 54% of the free float market capitalization of equities listed on the NSE. For the six-month period concluding in September 2024, the cumulative traded value of Nifty 50 index components constitutes approximately 27% of the total traded value of all equities on the NSE. Precise forecasting of stock changes within this index is essential for investors seeking to enhance their portfolios. Conventional statistical methods frequently encounter difficulties with the non-linear and intricate characteristics of financial data, prompting the investigation of machine learning and, more recently, deep learning methodologies. Hybrid models that combine different deep learning architectures have shown promise in capturing intricate patterns in stock price movements.

Despite advancements, several challenges persist in stock trend prediction. Various factors influence the financial markets, making it difficult to model their behavior accurately. Incorporation of qualitative data comprises of sentiment analysis from various news sources and published other sources into predictive models remains a complex task. Ensuring that models generalize well across different market conditions and do not overfit to specific patterns is a significant concern.

While existing studies have explored various deep learning models for stock prediction, gaps remain. Limited research has been conducted on combining multiple deep learning architectures to enhance predictive accuracy. Few studies have effectively integrated both macroeconomic and microeconomic sentiment data into predictive models. There is a limited of research work available for the Indian stock market with sentiment analysis data.

This study proposes developing a hybrid models that combine time series forecasting architectures based on Long Short-Term Memory (LSTM) networks, Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNN) along with sentiment analysis data. These models will process historical price data alongside sentiment information of various published information. The aim is to capture both quantitative and qualitative data which are effecting the stock price movements.

This research contributes theoretically how the hybrid deep learning models can be optimized for financial forecasting in the context of Indian stock market. Practically, the findings will help the financial analysts, retail traders while making appropriate trading decisions, potentially leading to more effective investment strategies. Additionally, the integration of sentiment analysis offers insights into the qualitative aspects influencing market dynamics.

II. Objective Of The Study

The research aims to find answers to following research questions ,

How can hybrid deep learning models be designed to effectively predict stock trends for the Indian stocks?
What is the impact of incorporating macroeconomic and microeconomic sentiment data on the predictive accuracy of these models?
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How can hybrid deep learning models be designed to effectively predict stock trends for the Indian stocks?
What is the impact of incorporating macroeconomic and microeconomic sentiment data on the predictive accuracy of these models?

What is the performance of the proposed models in compared to traditional methods while forecasting stock prices and trends?
The objectives of this study are the following:

- To create hybrid deep learning models that integrate various architectures to improve prediction accuracy for NIFTY 50 stocks.

- To integrate both macroeconomic and microeconomic sentiment data into the predictive models.

- To assess the models' performance in predicting stock prices and trends within the NIFTY 50 stocks

III. Literature Review

The Efficient Market Hypothesis (EMH) posits that "the valuation of a stock encapsulates all the information accessible to the market, rendering market predictions infeasible" [5]. Nevertheless, contemporary financial theory asserts that no market achieves perfect efficiency, thereby indicating that stock prices do not invariably represent their intrinsic value. In a similar vein, the returns of the Indian stock market do not manifest total randomness. It demonstrates a weak form of market efficiency, thus enabling the existence of predictions regarding the true value of stock prices [6].
Research conducted by Baker & Wurgler [7] has led to the conclusion that "investor sentiment exerts a significant influence on stock price fluctuations. Moreover, foreign stock exchange returns and their volatility exert an effect on the Indian stock market."
Aziz and Ahmad [8] explored the correlation between minimum daily returns and subsequent monthly returns within the time frame of 1999 to 2014 in the Indian stock market. Their findings suggest that the relationship between minimum daily returns and future stock returns is "dynamic and dependent on quantile, as determined through quantile regression analysis." They further proposed that, through the examination of historical data, future market predictions may be formulated in the context of the Indian stock market.
In the contemporary epoch characterized by Artificial Intelligence, the advent of Machine Learning concepts has stimulated researchers to develop various predictive models leveraging machine learning algorithms [9]. Machine Learning, as a subset of Artificial Intelligence, has garnered extensive academic scrutiny concerning the forecasting of stock market prices [10].
With the evolution of machine learning methodologies, including Deep Learning algorithms, predictive models have been refined to enhance the accuracy of stock market price forecasts [11, 12]. In the scholarly work conducted by Hirancha et al. [13], multiple deep learning algorithms, namely RNN, LSTM, and CNN, were employed to forecast the future stock price of TATA Motors, the NIFTY Index, and the S&P Index. Zahra, in his research, formulated LSTM-based predictive models that utilized the previous day's closing prices from various stock exchanges to forecast the subsequent day's closing price [14]. The comparative analysis indicates that LSTM-based predictive models exhibit superior accuracy in handling time series data than alternative deep learning frameworks [15]. Table 1 enumerates recent scholarly endeavors aimed at stock market prediction utilizing Deep Learning Algorithms.

TABLE I. THE WORKS OF LITERATURE REVIEWED IN THE FIELD OF STOCK MARKET PREDICTION. SOURCE: COMPILED BY AUTHORS

Reference	Dataset used	Additional Dataset	Algorithm Used	Result / Discussion	Year
[12]	Individual stocks	Stock price	CNN, LSTM	MAPE of LSTM is 1.98% and CNN is 2.16%	2018
[16]	Individual stocks	Open, High, Low and Close prices	SVM, LR, LSTM	Highest Accuracy of LSTM 63.59%	2019
[17]	NIFTY 50 index	Close price	CNN	Accuracy of 75.41%	2020
[18]	Indian Stock Market	Stock Price	Gaussian Naïve Bayes	Mean z-Score of 0.7032	2021
[19]	NIFTY 50 index	Previous day close price	LSTM	Accuracy through R^2 0.8388	2022
[14]	NIFTY 50 index	Open, High, Low and Close prices	CNN RNN LSTM	Highest R^2 of 0.819	2022
[20]	BSE & NSE IT Index	Index Price	LSTM	MAPE of 1.03%	2022
[21]	Indian Stock Market	Stock Price	KNN	Accuracy of seventy%	2022
[22]	Indian Stock Market	Stock price	LSTM Random Forest	MAPE of 1.36% for LSTM	2022
[23]	NIFTY 50 index	Technical Indicators	Decision Tree, Naïve Bayes, Random Forest, SVM LSTM	Highest Accuracy of 80.44% using LSTM	2023
[24]	NIFTY 50 index	Index Price & Chaos	Chaos+LSTM+PR	MAPE of 1.21	2023
[25]	USD/JPY	USD/JPY 5 mins data	RNN-ARIMA	Accuracy of seventy-six%	2020
[26]	US Individual stocks	Close price	LSTM	Accuracy scores between 52.23% to 89.44%	2020
[27]	US Individual stocks	Open, High, Low and Close prices	LSTM	Highest R^2 of 0.73	2021
[28]	Chinese Stock Index	Stock price	RNN, LSTM, GRU	Maximum Accuracy of 74% for LSTM	2022

a. Source: Compiled by Authors

IV. Data And Methodology

The experiment consists of data extraction, processing of data, Sentiment analysis using IBM Watson's Deep learning process, creation of Deep learning model based on LSTM algorithm to predict the future price, prediction of future price and evaluation of result. Fig. 2 represents the high-level Process flow diagram.

A Data ExtractionThe input data for the experiment is extracted for the period 29th November 2021 to 29th December 2023. The data related to published macro-economic information is taken majority from two leading Indian newspaper, The Economic Times and Hindustan Times. Also some amount of published data taken from Business Today and Thomson Reuters. The macro-economic data consist of major global stock market movements such as US, Japan, Hong Kong, European stock market, Crude oil price movements, Covid virus impacts, War escalations such as Russia/Ukraine, Middle East conflicts, US Actions of major central banks of western economics etc.

During the data preprocessing phase, any instances of duplicate data were systematically eradicated. The publicly available NIFTY 50 Index was sourced from the National Stock Exchange of India's official website. The NIFTY 50 index pricing encompasses the Open Price, Closing Price, High Price, and Low Price for each trading day (daily frequency) over the period from November 29, 2021, to December 29, 2023 [32].

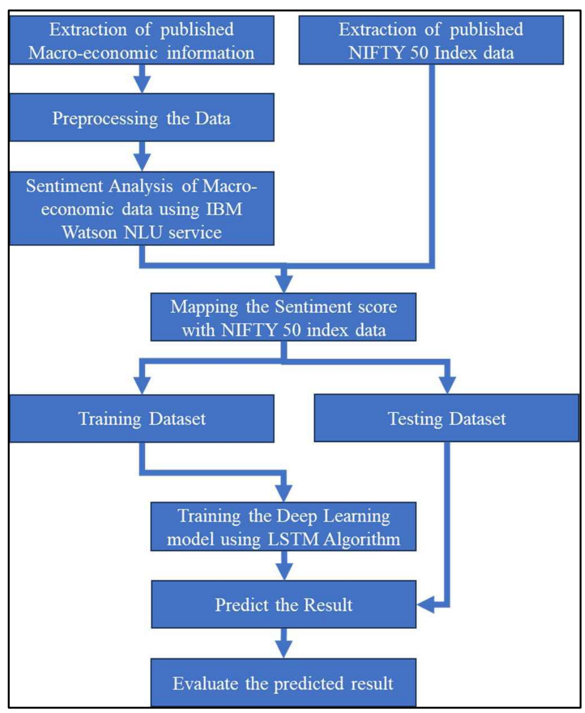

Fig. 1. The process flow diagram for the experiment set up.
Source: Compiled by Authors

B. Sentiment Analysis

To do the sentiment analysis of the pre-processed macro-economic data, IBM Watson's Natural Language Understanding(NLU) services has been used. IBM Watson NLU service processed each macro-economic input and provides a sentiment score along with a label for the sentiment.

The sentiment score ranges -1 to +1 and the label can be “Positive”, “Negative” or “Neutral” based on the sentiment score of the data. For a negative score, the sentiment label is negative, for a positive score, the sentiment is positive and for a zero score the sentiment is neutral. Once the sentiment analysis score is received, it has been aggregated based on date and NIFTY 50 index price.

C. Deep Learning based Prediction model

A python programming based multivariate Deep Learning model using LSTM Algorithm is constructed using the Keras library, which is a high-level Deep Learning API to access The Long Shrt-Term Memory (LSTM) model constitutes a specialized variation of the Recurrent Neural Network (RNN) architecture, specifically applicable to time series data [29].

"The LSTM architecture represents an effective resolution to the vanishing gradient issue associated with RNNs. It incorporates a memory cell capable of embodying long-term dependencies within sequential data. The LSTM memory cell is comprised of four distinct gates: the input gate, the output gate, the forget gate, and the self-recurrent neuron.” Figure 3 depicts the LSTM memory cell [2].

D. Evaluation of Result

The Augmented Dickey-Fuller (ADF) Test is used to identify stationarity of the input data series. The test is mathematically represented as,

$$D_t = \frac{\hat{\gamma}}{S(\hat{\gamma})} \quad (7)$$

Where D_t is the Dicky-Fuller test statistics, $\hat{\gamma}$ is the least square coefficient estimate of the coefficient, and $S(\hat{\gamma})$ the standard error of the least squares estimates of the coefficient from the regression model.

The predicted result is evaluated based on standard evaluation Metrics. Using Pearson’s Correlation, the potential linear correlation between the NIFTY 50 Index predicted and actual price is identified. The formula to calculate Pearson correlation coefficient is,

$$r = \frac{\sum(a_i-\bar{a})(b_i-\bar{b})}{\sqrt{\sum(a_i-\bar{a})^2 \sum(b_i-\bar{b})^2}} \quad (8)$$

Where r is the Pearson correlation coefficient, $\bar{a}$ and $\bar{b}$ are the mean of the values of a-series and b-series, a_i is the values of the a-series and b_i is the value of the b-series in a sample.

Further the strength of correlation between two variables is identified through coefficient of Determination, which is expressed as

$$R2 = (correlation\ coefficient)^2 \quad (9)$$

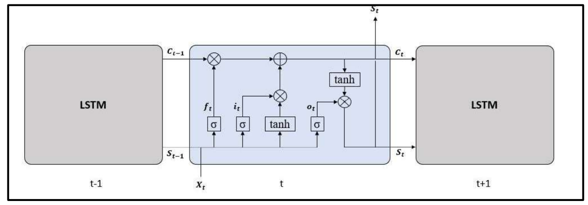

Fig. 2. The architecture of an LSTM Block

Source: Gers, F. A., Schmidhuber, J., & Cummins, F. (2002), Learning to forget: continual prediction with LSTM, 1999 Ninth International Conference on Artificial Neural Networks ICANN 99. 2, 850-855, doi: 10.1049/cp:19991218.

For the machine learning regression model the accuracy is evaluated using Root Mean Square Error (RMSE). It is expressed as,

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{b}_i - b_i)^2}{n}} \quad (11)$$

Where $\hat{b}_i$ is the i[th] prediction value, and b_i is the i[th] Actual value. To make it standardised, in the evaluation the Normalised Root Mean Square Error (NRMSE) is used using standard deviation sd,

$$NRMSE = \frac{RMSE}{sd} \quad (12)$$

To understand the difference between the predicted value and the actual value mean absolute error is used. The Mean Absolute error is expressed as below,

$$MAE = \frac{\sum_{i=1}^{n}\|\hat{b}_i - b\|}{n} \quad (13)$$

Where $\hat{b}_i$ is the prediction value of i[th] occurrence., and b_i is the Actual value of i[th] occurrence.

To understand the difference between the predicted value and the actual value in terms of percentage, Mean Absolute Percentage Error (MAPE) is used. It is expressed as,

$$MAPE = \frac{100\%}{n}\sum_{i=1}^{n}\frac{\|b_i - \hat{b}_i\|}{b_i} \quad (14)$$

Where $\hat{b}_i$ is the prediction value of i[th] occurrence., and b_i is the Actual value of i[th] occurrence.

V. Implementation of The Experiment

A. Sentiment Analaysis

The extracted macro-economic data is stored in an excel file. Using Python programming to process the IBM Watson Natural Language Understanding services, IBM Watson NLU python library is implemented. Against every row of data through the application programming interface (API) the IBM Watson NLU is fetched, which returns a sentiment score and sentiment label.

B. Predition of NIFTY 50 index price

The extracted stock price consist of OHLC data (Open, High, Low and Close price) along with

A multivariate Deep Learning model employing the Long Short-Term Memory (LSTM) algorithm has been developed utilizing the Keras library, which serves as a high-level Deep Learning API designed for interfacing with the TensorFlow Deep Learning Framework specifically for LSTM applications. The LSTM architecture is established with two LSTM layers comprising 60 and 50 LSTM units respectively, succeeded by a dropout layer implemented with a dropout rate of 0.2, in addition to a subsequent dense layer. An activation function has been incorporated into each LSTM layer to enhance model performance. The model is subjected to compilation through a stochastic gradient descent methodology, which facilitates the iterative adjustment of network weights based on the training dataset, while the associated loss is assessed for both training and validation datasets employing the Mean Squared Error metric. Hyperparameters, such as the number of epochs and batch size for the training dataset, are designated to govern the training process. In the evaluation phase, the model underwent testing with various combinations of parameters related to the LSTM layer configuration, including LSTM units, epochs, batch size, and an array of compiler options, aimed at discerning the optimized model configuration.

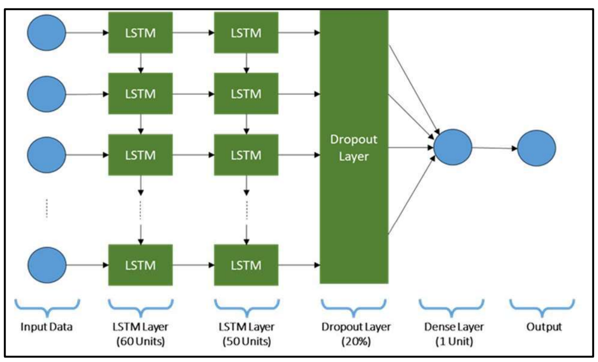

Fig. 3. LSTM based deep learning model for prediction

Source: Compiled by Authors

Vi. Evaluation Of Result And Discussion

The summary companies details for each sector is listed in the Table II.

Table III shows the descriptive statistics for training dataset which includes NIFTY 50 stock prices and respective sentiment analysis data.

With the sentiment score, the predicted Close price with sentiment data has better RMSE value compared to without sentiment data.

TABLE II. SUMMARY OF SECTORS OF COMPANIES COLLECTED

Industry	Number of Companies
Automobile and Auto Components	6
Capital Goods	1
Construction	1
Construction Materials	2
Consumer Durables	2
Consumer Services	1
Fast Moving Consumer Goods	5
Financial Services	11
Healthcare	4
Information Technology	5
Metals & Mining	4
Oil Gas & Consumable Fuels	4
Power	2
Services	1
Telecommunication	1
Total	50

Source: Compiled by Authors

During the execution of the model the Loss curve reached to 0.002 at 100th epochs. Figure 4 shows the curve of loss.

TABLE III. SUMMARY OF DESCRIPTIVE STATISTICS OF THE RESULT DATA

Descriptive Statistics						
	N	Minimum	Maximum	Mean	Skewness	Kurtosis
RMSE-With Sentiment	50	0.0082	0.0862	0.0259	1.842	3.411
MAPE-With Sentiment	50	0.6138	6.1240	1.9691	1.827	2.728
MAE-With Sentiment	50	2.7679	367.2127	47.4446	3.067	9.877
RMSE-Without Sentiment	50	0.0089	0.3228	0.0590	2.659	9.019
MAPE-Without Sentiment	50	0.7069	32.3110	4.8856	3.159	12.586
MAE-Without Sentiment	50	5.0861	988.3768	116.4351	2.928	10.110
Valid N (listwise)	50					

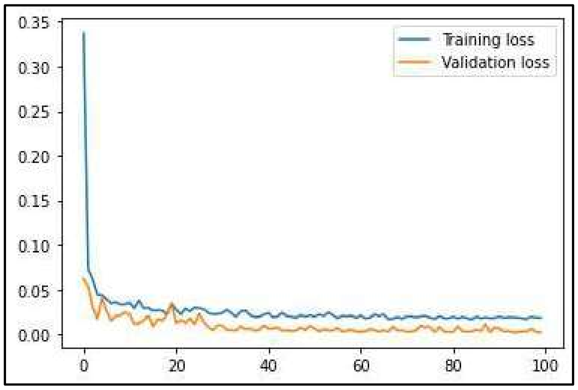

Fig. 4. Training loss and validation loss in the LSTM model.
Source: Compiled by Authors

Figure 5 depict the histogram of RMSE with sentiment data.

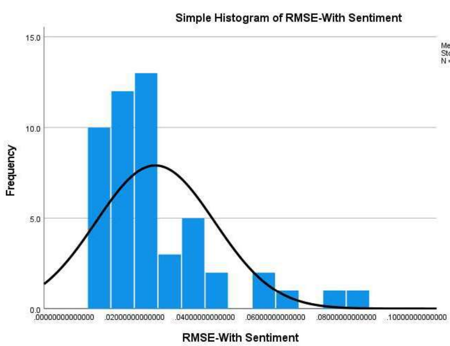

Fig. 5. Histogram data for RMSE with a nd without sentiment
Source: Compiled by Authors

Figure 6 depict the comparison of RMSE with sentiment data and without sentiment data for all the sectors.

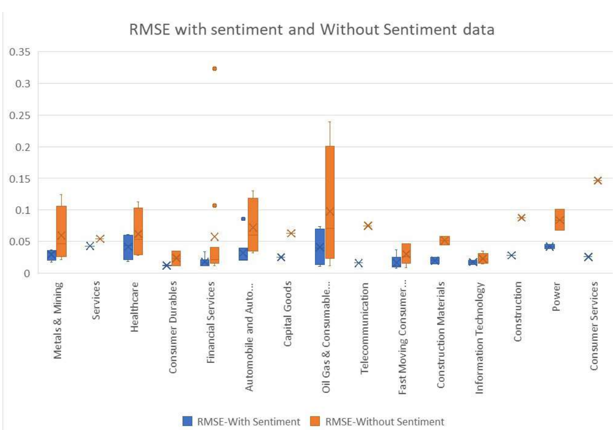

Fig. 6. Compasirion of RMSE for sentiment and without sentiment for all the sectors.
Source: Compiled by Authors

Figure 7 shows the specificity and sensitivity of the model execution. For all the three prediction (Positive, negative and neutral) the Area under the curve is more than 0.95. which is excellent performance of the model.

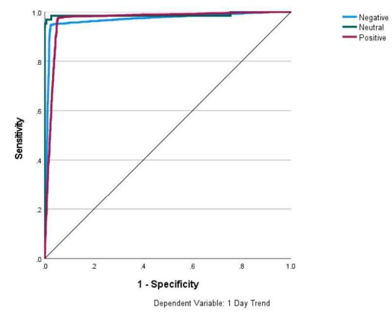

Fig. 7. Sensitivity vs Specoficity for the execution of the model

Figure 8 shows the importance factor of the variables used in the model.

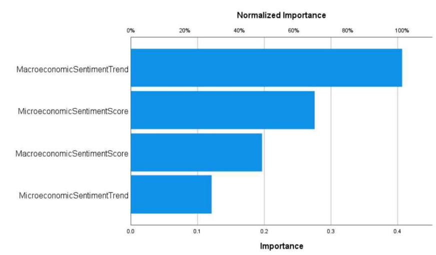

Fig. 8. Importance factors of the variables
Source: Compiled by Authors

Table IV summarizes the accuracy of the model performance. The model achieved 95.9% in training, 96.7% in Testing and 96.5% accuracy in the holdout or actual data.

TABLE IV. SUMMARY OF ACCURACY OF THE MODEL PERFROMANCE

Classification					
		Predicted			
Sample		Negative	Neutral	Positive	Percent Correct
Training	Negative	1692	0	108	94.0%
	Neutral	0	43	4	91.5%
	Positive	49	0	2013	97.6%
	Overall Percent	44.5%	1.1%	54.4%	95.9%
Testing	Negative	509	0	21	96.0%
	Neutral	0	16	0	100.0%
	Positive	18	0	604	97.1%
	Overall Percent	45.1%	1.4%	53.5%	96.7%
Holdout	Negative	241	0	14	94.5%
	Neutral	1	7	1	77.8%
	Positive	3	0	273	98.9%
	Overall Percent	45.4%	1.3%	53.3%	96.5%
Dependent Variable: 1 Day Trend					

a. Source: Compiled by Authors

Table V shows the performance summary of the model execution. The error percentage for the testing and holdout group is 3.5% and 3.3% respectively.

TABLE V. SUMMARY OF MODEL PERFROMANCE

Model Summary		
Training	Cross Entropy Error	670.009
	Percent Incorrect Predictions	4.10%
	Stopping Rule Used	1 consecutive step(s) with no decrease in errora
	Training Time	00:00.1
Testing	Cross Entropy Error	164.156
	Percent Incorrect Predictions	3.30%
Holdout	Percent Incorrect Predictions	3.50%
Dependent Variable: 1 Day Trend		

a. Source: Compiled by Authors

Table VI shows the summary of performance in comparison to other deep learning models. The accuracy, F1 Score, Precision and Recall data is higher in the proposed model comparison to other deep learning models.

TABLE VI. SUMMARY OF PERFROMANCE IN COMAPRAION TO OTHER DEEP LEARNING MODELS.

Model	Accuracy	F1 Score	Precision	Recall
Proposed Model	0.9658	0.9891	0.9512	0.9698
CNN	0.9457	0.9457	0.9463	0.9457
MLP	0.9448	0.9448	0.9453	0.9448
Gradient Boosting	0.9422	0.9421	0.9426	0.9422
RNN	0.9413	0.9411	0.9424	0.9413
SVM	0.9359	0.9358	0.9369	0.9359
Naïve Bayes	0.8995	0.8992	0.9008	0.8995

a. Source: Compiled by Authors

The table VII shows the result of Related samples Wilcoxon signed rank test. The results shows all the performance indicators have improved results.

TABLE VII. RELATED SAMPLES WILCOXON SIGNED RANK TEST

Related-Samples Wilcoxon Signed Rank Test Summary				
Description	RMSE	MAPE	MAE	R2
Total N	50	50	50	50
Test Statistic	1275.000	1270.000	1272	556.000
Standard Error	103.592	103.592	103.592	103.592
Standardized Test Statistic	6.154	6.106	6.125	-0.787
Asymptotic Sig.(2-sided test)	<0.001	<0.001	<0.001	0.431

a. Source: Compiled by Authors

VII. Conclusion

In this research we have used sentiment of macro-economic information and microeconomic information using machine learning approaches and using the sentiment analysis score tried to correlate the trend of stocks of NIFTY 50 . Furthermore, we have tried to predict the stock trend and stock closing price. Using various hybrid deep learning models such as LSTM, CNN, RNN etc, along with sentiment analysis data we have implemented a fusion prediction model to forecast the next day Close price of the NIFTY 50 stocks. The results shows the hybrid model having sentiment analysis with LSTM achieved highest accuracy in comparison to other models.

Our research will help the retail investors
and other traders who participate in the Indian stock market, particularly in the index instruments through its derivative segment or Index funds, as they will utilise the predictions to understand the next-day Open and close prices of the index, based on the sentiment of global macro-economic changes. They can anticipate the trend of market based on the sentiment score and act on their investment decisions accordingly

Further studies can be initiated to include micro-economic information to understand the sentiment of the data and its impact on various indices price. Similar study on stock prices can be initiated to understand the performances.

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