Stock Market Prediction Using Multi-Filtered LSTM Approach

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***Abstract*—This research explores the application of various technical indicators, including the Relative Strength Index (RSI), Bollinger Bands, the Volatility Index (VIX), and the Grandfather-Father-Son (GFS) trading strategy, in conjunction with Long Short-Term Memory (LSTM) networks for stock market prediction. The study focuses on the 10 major NSE sectors and their corresponding companies using historical stock price data obtained from Yahoo Finance spanning from January 1, 2020 to the present. Additionally, live data is continuously incorporated to enhance real-time predictive accuracy. After filtering using the technical indicators and the trading strategy, web scraping is employed to perform sentiment analysis by categorizing information as positive, negative, or neutral. The primary objective is to develop a multi-timeframe predictive system that leverages an LSTM network with three layers (each with 32 units) and a dense output layer, optimized using the Adam optimizer with mean squared error (MSE) as the loss function and evaluated by the R^2 score metric. Our main aim is to integrate technical indicators and the trading strategy to refine the selection of NSE sectors and corresponding companies, surpassing existing methodologies in accuracy, reliability, and effectiveness, ultimately reducing losses and maximizing profits for traders and investors.**

***Index Terms*—LSTM, Technical Indicators, Grandfather-Father-Son (GFS) Trading Strategy, Web Scraping, Sentiment Analysis, Stock Market Prediction, Deep Learning, Financial Analysis, Time Series Data, Multi-Filtered Approach.**

I. Introduction

The stock market has undergone significant changes over the past few decades, evolving into one of the most complex and volatile financial systems [19]. These challenges make market prediction extremely difficult but critically important for investors [13], [31]. In the context of Indian markets, research has identified unique characteristics such as high volatility and increased market participation [4], [17], [25]. Studies of indices like Nifty50 and SENSEX have helped investors understand these challenges and opportunities [25], [30]. The sensitivity of the market to domestic news as well as global trends further motivates the need for advanced predictive modeling [28].

Technical indicators play a powerful role in identifying market trends and momentum. Indicators such as the Relative Strength Index (RSI) and Bollinger Bands are critical for signaling trend reversals and potential entry or exit points [2], [12], [23]. Moreover, investors have progressively adopted hybrid systems that combine multiple indicators to generate sophisticated trading signals [3], [14], [33].

Recent advancements in machine learning and artificial intelligence have revolutionized stock market forecasting. Deep learning models, particularly Long Short-Term Memory (LSTM) networks, have been shown to effectively model financial time series data [7], [8], [10]. The ability of LSTM networks to learn from sequential data makes them ideal for predicting stock prices over short intervals such as one week (Monday to Friday) [7], [35]. In addition, the integration of sentiment analysis—especially pertinent to Indian markets where local news can have a strong impact—further enhances predictive performance [1], [20], [24]. Recent studies suggest that combining machine learning models, technical indicators, and sentiment analysis leads to improved accuracy and reduced financial loss [24], [34], [39].

II. LITERATURE SURVEY

The author objective is to predict stock trends using deep learning models in his approach he took three Indian banks those are HDFC, Yes Bank and SBI from 2008-2018 and by combining deep learning model and technical indicators and the findings that he got from the prediction is for HDFC he got 63.59 percent prediction and for the YES bank he got

56.23 percent and for the SBI bank he got 57.95 percent the conclusion that he proposed is by combing deep learning model with technical indicators help the investors to take profitable trades.[33]

In, This paper the author objective is to find the impact of news sentiment on Indian stock markets. The author took the sentiment data from a company called meltwater, which provides the necessary information about the company's present in stock market. the author had collected The Hindu, Equity Bulls, India Infoline Ltd,Webindia123.com, Finanzen.net, Moneycontrol, Rediff.com,InvestmentGuruIndia.com, Yahoo! India News, NDTV.com, eNewsHub, etc. and the final conclusion that the author made was that there is no causal relationship between the sentiments extracted from the internet news and the performance of the Indian stock markets [28] [41] .

The author is predicting the stock market using the interrelated time-series data. Observing various kinds of international markets based on his study, he concluded that his model can predict stock directions well in the manufacturing industry and the method he followed is the evaluation strategy [27]

The authors trying to find the stock closing price using LSTM in time series data took the Microsoft stock as an option and the data set they took from 1990-2017 with features like Open value, Close value, High value, Low value. and they achieve 71percent accuracy with minimal loss. In conclusion, they said that LSTM effectively captures market trends and the accuracy can be increased with sentiment analysis. [36]

In, this paper the author is trying to find the Stock market prediction and LSTM algorithm and technical indicators as voters. in this paper the author used multiple technical indicators like MA,RSI,BB,RMSE by taking these technical indicators is voters the prediction is done for Apple stock and data is taken from 1984-2017. Based on his research, he concluded that combining technical indicators as voters and using the LSTM algorithm for prediction gave good results [23] .

In this paper the author trying to find the NSE Stock Market Prediction Using Deep Learning Models The idea that is proposing is comparing deep learning models like (MLP, RNN, LSTM, CNN) for stock prediction the author chooses two indices NSE and NYSE. The author took six companies TATA Motors, Maruthi, HCL,Axis Bank,BAC,CHK as a conclusion, the author is stating that CNN is ideal for stock prediction due to its ability to learn localized patterns. [4]

Compared to the other research papers, our paper introduces a border and better approach for stock market prediction while most existing studies focused on a set of individual stocks like as HDFC, Yes Bank, SBI etc. the approach we followed expands the scope to major NSE sectors and dynamically filtering stocks based on multi-time frame analysis. Unlike, who applied technical indicators or compared deep learning models on specific stocks or indices. Our proposed method combines multiple indicators like (RSI, Bollinger bands and VIX) with a trading strategy called GFS(Grandfather-Father-Son) and we also included news sentiment analysis via web scrapping and integrates it with the stock selection process, ensuring that only positively trending news influences predictions. Finally, our closing statement is that our project sets itself apart by integrating technical analysis, sentiment filtering, and LSTM in a pipeline manner where it bridges AI research with real-world stock trading practices, offering a more scalable, flexible, and minimizing loss trades .

III. RELATED TERMINOLOGIES

A. Stock Technical Indicators (STIs)

These are statistical estimates based on a share's price, volume, or value. They are not dependent on a business's details, like profit, margin, revenue, or earnings. Technical analysts consider that price patterns can be recognized from historical figures and are generally based on trends. Analysts derive indicators by analyzing historical data to predict future price movements. Active stock traders commonly use STIs to study short-term price movements, and long-term investors use STIs to recognize buy or sell periods. STIs can be combined with trading systems and are beneficial while forecasting stocks' future prices.[40] .

The technical indicators are two types: The overlays use the same scale as prices. Examples include Bollinger Bands. The Oscillators oscillate between a local minimum and maximum and are plotted above or below a price chart. RSI is a typical example. For removing the noise from stock data that occurs due to price variations, this work utilizes VIX to smooth out prices. It is also called a lagging or trend-following indicator as it is calculated from past prices.[40] .

In the above Tab. 1 is the current price of the day under consideration, SMA is the Simple Moving Average over a selected period, UB and LB are the Upper and Lower Bollinger Bands, respectively. RSI is the Relative Strength Index calculated based on average gain (AG) and average loss (AL) over the past period. Additionally, VIX represents market volatility, indicating the expected fluctuation in stock prices. .[40]

Indicator	Formula
Simple Moving Average (SMA)	$SMA = \frac{\sum C_i}{N}$
Standard Deviation (σ)	$\sigma = \sqrt{\frac{\sum (C_i - SMA)^2}{N}}$
Upper Bollinger Band (UB)	$UB = SMA + (k \times \sigma)$
Lower Bollinger Band (LB)	$LB = SMA - (k \times \sigma)$
Average Gain (AG)	$AG = \frac{\sum \text{Gain over N days}}{N}$
Average Loss (AL)	$AL = \frac{\sum \text{Loss over N days}}{N}$
Relative Strength (RS)	$RS = \frac{AG}{AL}$
Relative Strength Index (RSI)	$RSI = 100 - \left(\frac{100}{1+RS}\right)$
Volatility Index (VIX)	$VIX = 100 \times \sigma$

Tab.1: Combined technical indicators and their formulas

B. Trading Strategy

The trading strategy that we're going to use in our research is the GFS trading strategy. GFS stands for Grandfather-Father-Son. This is a multi-timeframe trading strategy that analyzes price movements across daily, weekly, and monthly charts. This method helps traders make informed decisions by aligning short-term price movements with broader market trends.

The Grandfather-Father-Son (GFS) Trading Strategy is a powerful approach for traders looking to balance long-term market direction with short-term trade execution. By analyzing three time frames, traders can make more confident and profitable trading decisions. This strategy is also known as the swing trading method. Based on the three different time frames (Monthly, Weekly, and Daily), this is used when the price of an asset moves within a horizontal range without showing a clear uptrend or downtrend.

Why is it important to use a trading strategy in the stock market? We have observed in our research that the swing trading method can help in minimizing the risk and improving the accuracy. The technical indicators that are used in our approach are closely connected to this trading strategy. Since we have set up strong constraints, the GFS strategy becomes a valuable component of our model. It helps us filter out sectors and related stocks while eliminating unrelated ones.

By applying this process, we can identify top-performing sectors from a group of sectors under consideration. Once we obtain these top sectors, we then analyze the stock companies within them and extract the top-performing stocks, ensuring a refined and structured stock selection process.

Using the GFS Trading Strategy significantly improves decision-making by:

- Reducing risk through trend confirmation
- Improving trade accuracy and stock selection
- Providing a structured, data-driven approach

IV. METHODOLOGY

The goal is to identify the top-performing sectors and the top-performing stock company within those sectors. This will be done through a filtration process, which consists of technical indicators and a multi-timeframe trading strategy. Following this, we will use our model to predict top-performing stocks' closing, high, and low prices for up to five days. The data that we are using is registered in the National Stock Exchange, India.

A. Dataset Collection

In our research, we primarily focused on sectors and the stock companies within those sectors that were registered in the NSE. Details of sectors and the stock companies within those sectors are shown in Tables 1,2,3,4,5,6,7,8,9,10, and 11.

TABLE I
SECTOR INDICES AND THEIR TICKER SYMBOLS

Index Code	Index Name
N̂SEI	NIFTY 50
ĈNXAUTO	NIFTY AUTO
N̂SEBANK	NIFTY BANK
ĈNXFMCG	NIFTY FMCG
ĈNXIT	NIFTY IT
ĈNXMETAL	NIFTY METAL
ĈNXPHARMA	NIFTY PHARMA
ĈNXREALTY	NIFTY REALTY
ĈNXMEDIA	NIFTY MEDIA
ĈNXCONSOM	NIFTY CONSUMER GOODS

TABLE II
AUTOMOBILE (ĈNXAUTO)

TATAMOTORS.NS	MARUTI.NS	M&M.NS
HEROMOTOCO.NS	EICHERMOT.NS	BAJAJ-AUTO.NS
TVSMOTOR.NS	MOTHERSON.NS	BHARATFORG.NS
TATAMTRDVR.NS	BOSCHLTD.NS	MRF.NS
BALKRISIND.NS	EXIDEIND.NS	APOLLOTYRE.NS
ASHOKLEY.NS		

TABLE III
FMCG (ĈNXFMCG)

HINDUNILVR.NS	DABUR.NS	ITC.NS
BRITANNIA.NS	NESTLEIND.NS	TATACONSUM.NS
VBL.NS	GODREJCP.NS	COLPAL.NS
UNITDSPR.NS	MARICO.NS	PGHH.NS
UBL.NS	RADICO.NS	BALRAMCHIN.NS

TABLE IV
INFORMATION TECHNOLOGY (ĈNXIT)

TCS.NS	INFY.NS	WIPRO.NS
HCLTECH.NS	TECHM.NS	LTIM.NS
PERSISTENT.NS	MPHASIS.NS	LTTS.NS

TABLE V
BANKING (N̂SEBANK)

HDFCBANK.NS	ICICIBANK.NS	AXISBANK.NS
KOTAKBANK.NS	SBIN.NS	INDUSINDBK.NS
FEDERALBNK.NS	PNB.NS	BANKBARODA.NS
AUBANK.NS	IDFCFIRSTB.NS	BANDHANBNK.NS

TABLE VI
METALS (ĈNXMETAL)

TATASTEEL.NS	JSWSTEEL.NS	HINDALCO.NS
COALINDIA.NS	VEDL.NS	JSL.NS
ADANIENT.NS	NMDC.NS	SAIL.NS
HINDZINC.NS	HINDCOPPER.NS	APLAPOLLO.NS
RATNAMANI.NS	WELCORP.NS	

TABLE VII
PHARMACEUTICALS (ĈNXPHARMA)

SUNPHARMA.NS	CIPLA.NS	DRREDDY.NS
LUPIN.NS	AARTIIND.NS	AUROPHARMA.NS
TORNTPHARM.NS	MANKIND.NS	IPCALAB.NS
ALKEM.NS	DIVISLAB.NS	LAURUSLABS.NS
ABBOTINDIA.NS	ZYDUSLIFE.NS	NATCOPHARM.NS
GLAND.NS	BIOCON.NS	GLENMARK.NS
SANOFI.NS	JBCHEPHARM.NS	GRANULES.NS

TABLE VIII
REAL ESTATE (ĈNXREALTY)

DLF.NS	GODREJPROP.NS	OBEROIRLTY.NS
BRIGADE.NS	LODHA.NS	PRESTIGE.NS
SOBHA.NS	MAHLIFE.NS	PHOENIXLTD.NS
SUNTECK.NS		

TABLE IX
MEDIA (ĈNXMEDIA)

ZEEMEDIA.NS	SUNTV.NS	TV18BRDCST.NS
SAREGAMA.NS	NETWORK18.NS	NAZARA.NS
PVRINOX.NS	DISHTV.NS	HATHWAY.NS

TABLE X
CONSUMER DURABLES (ĈNXCONSUM)

TITAN.NS	POLYCAB.NS	BLUESTARCO.NS
CROMPTON.NS	VOLTAS.NS	DIXON.NS
KAJARIACER.NS	KALYANKJIL.NS	CERA.NS
VGUARD.NS	HAVELLS.NS	BATAINDIA.NS
WHIRLPOOL.NS	CENTURYPLY.NS	RAJESHEXPO.NS

TABLE XI
NIFTY 50 INDEX (N̂SEI)

ADANIENT.NS	ADANIPORTS.NS	APOLLOHOSP.NS
ASIANPAINT.NS	AXISBANK.NS	BAJAJ-AUTO.NS
BAJFINANCE.NS	BPCL.NS	BHARTIARTL.NS
BRITANNIA.NS	CIPLA.NS	COALINDIA.NS
DIVISLAB.NS	DRREDDY.NS	EICHERMOT.NS
GRASIM.NS	HCLTECH.NS	HDFCBANK.NS
HDFCLIFE.NS	HEROMOTOCO.NS	HINDALCO.NS
HINDUNILVR.NS	ICICIBANK.NS	INDUSINDBK.NS
INFY.NS	ITC.NS	JSWSTEEL.NS
KOTAKBANK.NS	LT.NS	LTIM.NS
M&M.NS	MARUTI.NS	NESTLEIND.NS
NTPC.NS	ONGC.NS	POWERGRID.NS
RELIANCE.NS	SBILIFE.NS	SBIN.NS
SUNPHARMA.NS	TCS.NS	TATACONSUM.NS
TATAMOTORS.NS	TATASTEEL.NS	TECHM.NS
TITAN.NS	ULTRACEMCO.NS	UPL.NS
WIPRO.NS		

Our target is to analyze and identify strong-performing stocks by looking into all 10 sectors and the companies within those sectors. For our analysis, we used APIs provided by Yahoo Finance to extract stock dataset of these companies for the last 5 years till today's date (2021 to 2025) using company symbols as tickers. Dataset includes several attributes like Date, Open, High, Low, Close, Adj. Close, etc. We are primarily using the closing price as the main input, as we are interested in predicting not only the closing price but also the high and low prices of the companies.

B. Dataset Insights

We extracted stock details using Yahoo Finance API, which included companies listed under all 10 sectors registered in the NSE. The dataset spans the last five years and includes historical stock information for each company. Some companies may have limited data due to recent NSE listings. Our approach uses historical data to predict future high, low, and closing prices based on each company's performance and sector-wise grouping. .

C. Evaluation Metrics

We are focused on two evaluation metrics for performance Evaluation: RMSE and R²

Root Mean Square Error/Deviation (RMSD) : It is most com- monly used metric to find the difference between the actual values vs predicted values. RMSD represents the square root of actual value vs predicted value.[42]

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_i - \hat{X}_i)^2} \tag{1}$$

R² Score: Determines how well the model's predictions fit the actual data.

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(X_i - \hat{X}i)^2}{\sum i = 1^N (X_i - \bar{X})^2} \tag{2}$$

where:

- X_i = actual value,
- $\hat{X}_i$ = predicted value,
- $\bar{X}$ = mean of actual values,
- N = number of observations.

D. Machine Learning Models

In our research work, we have worked on 2 types of ML-based models: LSTM, NLP (Natural Language Processing) for web scraping and sentiment analysis. Hyperparameters of these models were tuned before finally testing our dataset. .

NLP for web scraping and sentiment analysis .

To improve stock price prediction, our model uses NLP techniques for sentiment analysis of financial news. Using web scraping methods, we extract stock-related news articles from various financial portals and resources to analyze their sentiments through VADER and FinBERT models.

The sentiment scores are classified as Positive, Negative, or Neutral, which helps identify market trends and investor sentiment. These insights are incorporated into our predictive model to improve accuracy by factoring in external market influences beyond historical price movements. .

Long-Short Term Memory .

LSTM is an abbreviation for Long-Short Term Memory,and it is basically a type of neural network. LSTM models are basically a special type of RNN models that uses some special unit apart from other RNN units. LSTM consist of a LSTM architecture picture. memory cell that helps it to store information of data from longer time.[42] .

These cells include can store historical information and thus are extensively used in time series problems.There are three basic gates in LSTM model :

- Input: Decides when information comes through this gate.
- Forget: Decides which information and how much should be kept and passed to the next layer.
- Output: Determines the value of next hidden state.

. This model was proposed to overcome the problem of vanishing gradient in RNN models. LSTM model also has gates which are the deciding factor in whether an information is to be stored and moved to next cell or ignored. We have used Keras library for implementing our LSTM model.[42] .

LSTM Cell .

The computations in an LSTM cell can be defined by the following equations:

$$i_t = \sigma(W_i H + b_i) \tag{1}$$
$$f_t = \sigma(W_f H + b_f) \tag{2}$$
$$o_t = \sigma(W_o H + b_o) \tag{3}$$
$$\tilde{c}_t = \tanh(W_c H + b_c) \tag{4}$$
$$c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t \tag{5}$$
$$h_t = \tanh(c_t) \odot o_t \tag{6}$$

where:

- i_t is the input gate,
- f_t is the forget gate,
- o_t is the output gate,
- $\tilde{c}_t$ is the candidate cell state,
- c_t is the cell state,
- h_t is the hidden state (also called memory),
- σ is the sigmoid function,
- $\tanh$ is the hyperbolic tangent function,
- $\odot$ denotes element-wise multiplication.

V. RESULTS & DISCUSSION

The VIX is used to reconfirm the general market volatilities. This module uses yfinance to access the latest closing value of VIX. The project aims at getting an early warning about the state of the market. When the VIX goes up, we get warned to be careful because the markets are behaving erratically. This basic check is a precursor to additional analyses.

Following is the technical analysis part. The code uses historical stock prices and cleans them by resetting the index and making column names consistent. It also removes numeric type and null data. After which, the important technical indicators like 14-day Relative Strength Index (RSI) and Bollinger Bands are calculated. These indicators measure how much stocks move up or down, and how strong that upward or downward force is. We analyze them daily, weekly, and monthly. The multi-time frame strategy covers all the key intervals.

The third module, GFS or Grandfather-Father-Son Analysis, was created to prepare a report from technical analysis. This script reads a list of stock symbols from a CSV file and then calculates the daily, weekly, and monthly technical indicators. The stocks are filtered and analysed whether their RSI values are balanced (generally between 40 and 60) or not. This is done to ensure that the stocks are not overbought or oversold and hence flag the ones with balanced momentum. The output is a table-format report with qualified indices and stocks placed appropriately.

And then there is the sentiment news analysis module. Here, the software extracts news headlines from sources such as Moneycontrol and Bing. It then makes use of either VADER or FinBERT to determine the sentiment of each headline. This is the point where the determination is made of whether news sentiment towards a company is positive, negative, or neutral. If the sentiment of a company is extremely negative, the company is excluded from further consideration. This is so that the stocks chosen for the prediction stage are unlikely to be negatively affected by negative news.

The final module is the LSTM analysis which handles the price prediction. It starts by preprocessing data again: sorting dates, scaling closing prices with MinMaxScaler, and converting data into sequences that can be interpreted by the LSTM model. The network consists of a sequence of LSTM layers to see the time-dependent trends in data, and the dense layers which finally predict the next day's price. The model is trained with Adam optimizer and mean squared error loss, and after training, makes future price predictions along with a simple evaluation metric like R^2 scores for the train and test set.

These parts are all integrated into a live Streamlit web application where the user can edit data, review reports, perform sentiment analysis, and ultimately display visualizations of the price projections along with comparison graphs and tables of future projections.

indexcode	indexname	dayrsi14	weekrsi14	monthrsi14	dltp	daylowerband	daymiddleband	weeklowerband	weekmiddleband	monthlowerband	monthmiddleband
^NSEI	NIFTY 50	56.8	48.66	58.75	23332.35	21919.59	22927.9	22094.58	23434.35	19302.65	22811.4
^CNXMETAL	NIFTY METAL	58.17	52.94	55.11	9080.05	8547.38	8977.78	8042.85	8764.33	4764.23	5780.79

Figure 1 Qualified Indices

This table contains filtered index data for NIFTY 50 and NIFTY METAL, showcasing values like RSI (s14), Bollinger Bands, and daily last traded prices.

indexcode	indexname	dayrsi14	weekrsi14	monthrsi14	daylowerband	daymiddleband	weeklowerband	weekmiddleband	monthlowerband	monthmiddleband
^NSEI	BAJAJ-AUTO.NS	53.83	41.15	53.62	7181.86	7720.16	7465.62	8561.22	4962.43	8407.24
^NSEI	CIPLA.NS	45.2	47.22	58.16	1405.54	1470.99	1402.39	1467.54	1157.92	1430.5
^NSEI	DRREDDY.NS	45.54	42.68	50.91	1091.63	1149.6	1061.58	1226.85	1011.93	1206.87
^NSEI	HINDALCO.NS	46.53	51.93	57.5	651.66	683.62	566.87	638.29	460.54	617.85
^NSEI	HINDUNILVR.NS	48.49	40.22	44.81	2149.34	2218.18	2136.88	2340.17	2053.63	2436.35
^NSEI	MARUTI.NS	45.95	47.97	55.28	11435.43	11655.19	10552.27	11765.23	9671.62	11560.12
^NSEI	RELIANCE.NS	50.01	44.64	48.06	1181.92	1248.78	1195.25	1254.36	1086.42	1342.19
^NSEI	TITAN.NS	48.75	42.08	48.96	2966.86	3066.57	2960.28	3285.74	2931.58	3404.82
^CNXMETAL	HINDALCO.NS	46.53	51.93	57.5	651.66	683.62	566.87	638.29	460.54	617.85

Figure 2 Qualified Stocks

These are the financial data for various stocks under the NSEI and CNXMETAL indices, including key technical indicators like Bollinger Bands and trend percentages.

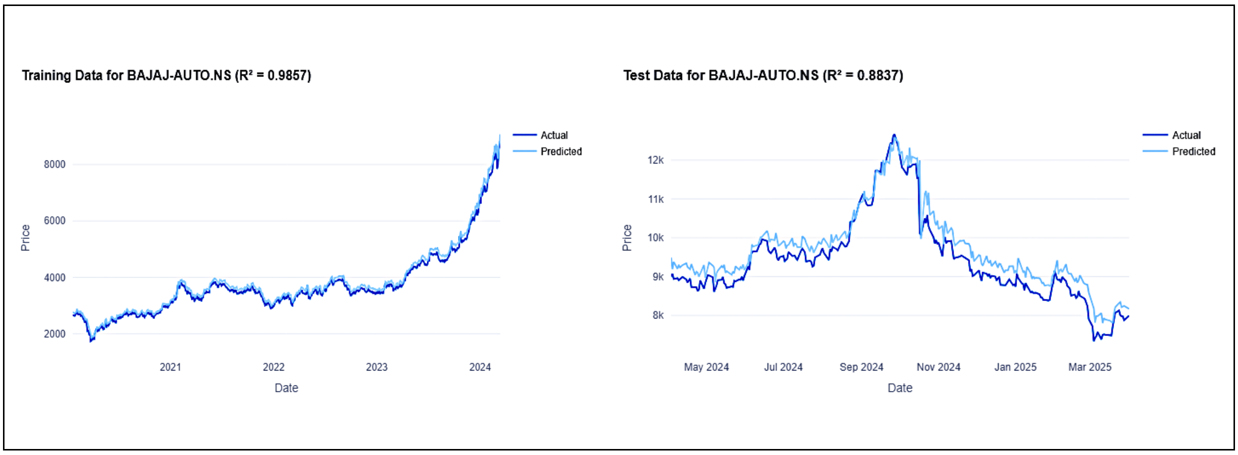

Figure 3 Bajaj-Auto

Date	Predicted Close	Predicted High	Predicted Low
2025-04-03 00:00:00	8,387.9932	8,446.1025	8,333.0225
2025-04-04 00:00:00	8,709.5820	8,767.6914	8,654.6113
2025-04-07 00:00:00	8,964.0625	9,022.1719	8,909.0918
2025-04-08 00:00:00	9,145.6465	9,203.7559	9,090.6758
2025-04-09 00:00:00	9,268.5332	9,326.6426	9,213.5625

The predicted prices show an upward trend, indicating positive market momentum for Bajaj Auto. The proximity of the high and low values suggests reliable, consistent predictions across the forecast period.

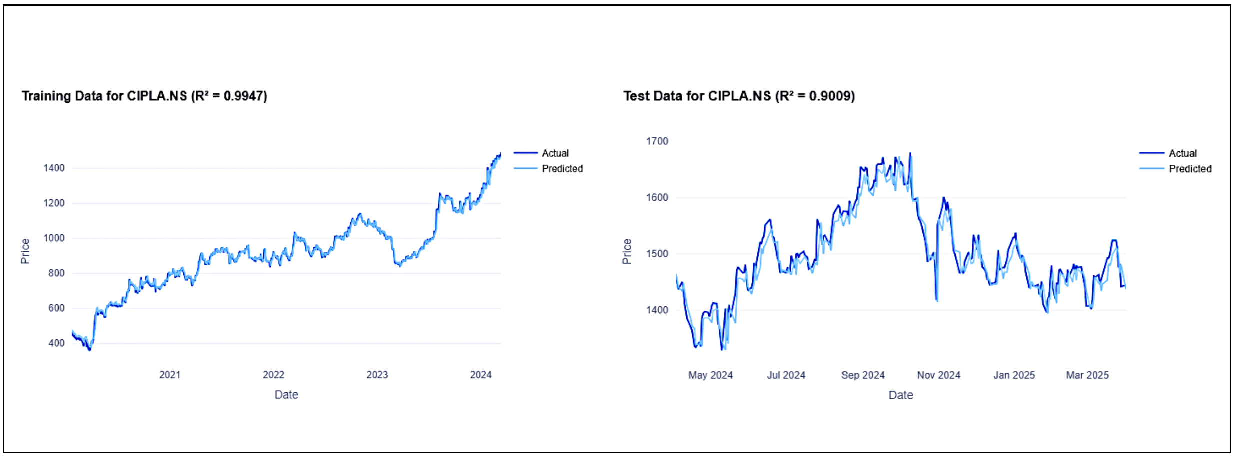

Figure 4 Cipla

Date	Predicted Close	Predicted High	Predicted Low
2025-04-03 00:00:00	1,454.1055	1,466.4478	1,442.7775
2025-04-04 00:00:00	1,452.5894	1,464.9316	1,441.2614
2025-04-07 00:00:00	1,449.1022	1,461.4445	1,437.7742
2025-04-08 00:00:00	1,444.7234	1,457.0657	1,433.3954
2025-04-09 00:00:00	1,440.1182	1,452.4604	1,428.7902

The predicted prices show an upward trend, indicating positive market momentum for Bajaj Auto. The proximity of the high and low values suggests reliable, consistent predictions across the forecast period.

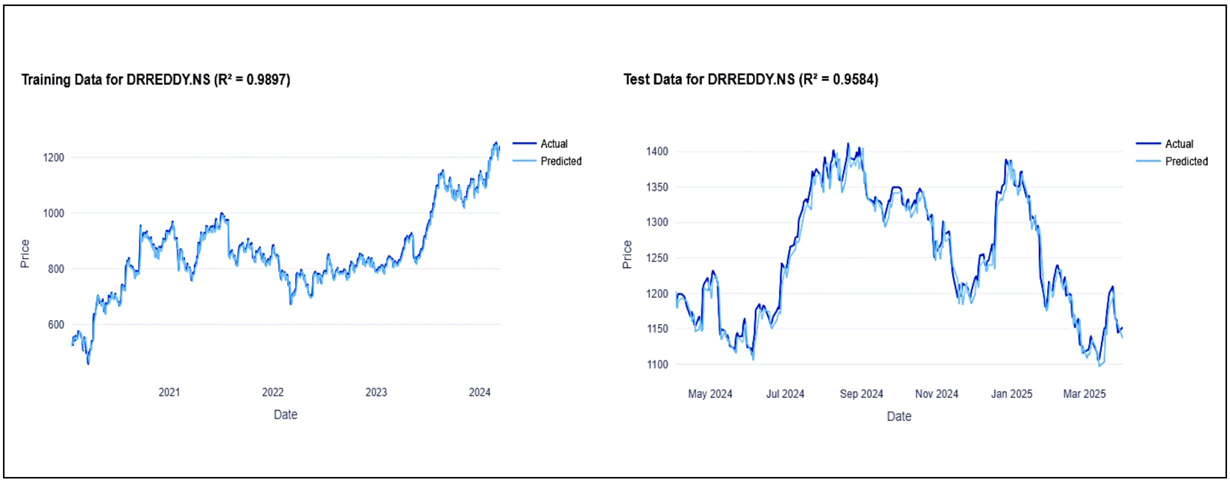

Figure 5 DrReddy's

Date	Predicted Close	Predicted High	Predicted Low
2025-04-03 00:00:00	1,142.7122	1,153.3590	1,132.7787
2025-04-04 00:00:00	1,136.3572	1,147.0040	1,126.4237
2025-04-07 00:00:00	1,129.6112	1,140.2581	1,119.6777
2025-04-08 00:00:00	1,122.8556	1,133.5024	1,112.9221
2025-04-09 00:00:00	1,116.1215	1,126.7683	1,106.1880

The predicted prices show an upward trend, indicating positive market momentum for Bajaj Auto. The proximity of the high and low values suggests reliable, consistent predictions across the forecast period.

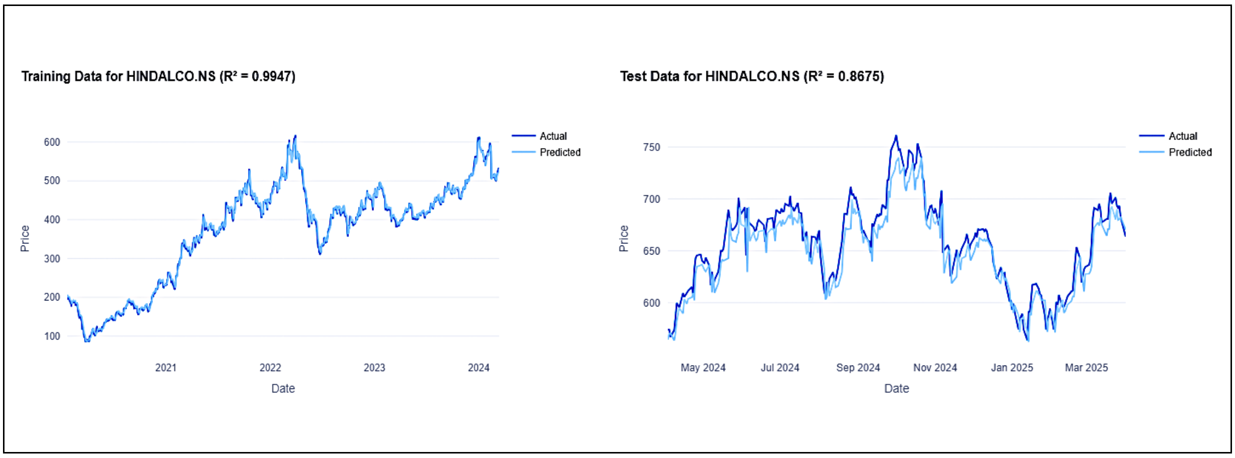

Figure 6 HINDALCO

Date	Predicted Close	Predicted High	Predicted Low
2025-04-03 00:00:00	654.9755	661.3879	648.8666
2025-04-04 00:00:00	647.9478	654.3602	641.8389
2025-04-07 00:00:00	641.5894	648.0018	635.4805
2025-04-08 00:00:00	635.8452	642.2576	629.7363
2025-04-09 00:00:00	630.5795	636.9919	624.4706

The predicted prices show an upward trend, indicating positive market momentum for Bajaj Auto. The proximity of the high and low values suggests reliable, consistent predictions across the forecast period.

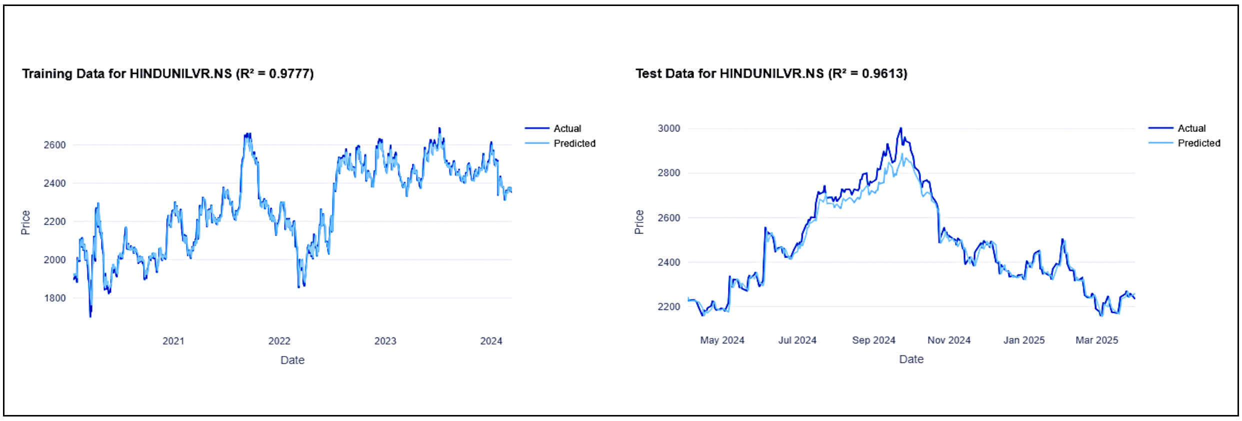

Figure 7 HINDUNILVR

Date	Predicted Close	Predicted High	Predicted Low
2025-04-03 00:00:00	2,237.4297	2,260.6960	2,215.1238
2025-04-04 00:00:00	2,235.4832	2,258.7495	2,213.1772
2025-04-07 00:00:00	2,233.1123	2,256.3787	2,210.8064
2025-04-08 00:00:00	2,230.4607	2,253.7271	2,208.1548
2025-04-09 00:00:00	2,227.6599	2,250.9263	2,205.3540

The predicted prices show an upward trend, indicating positive market momentum for Bajaj Auto. The proximity of the high and low values suggests reliable, consistent predictions across the forecast period.

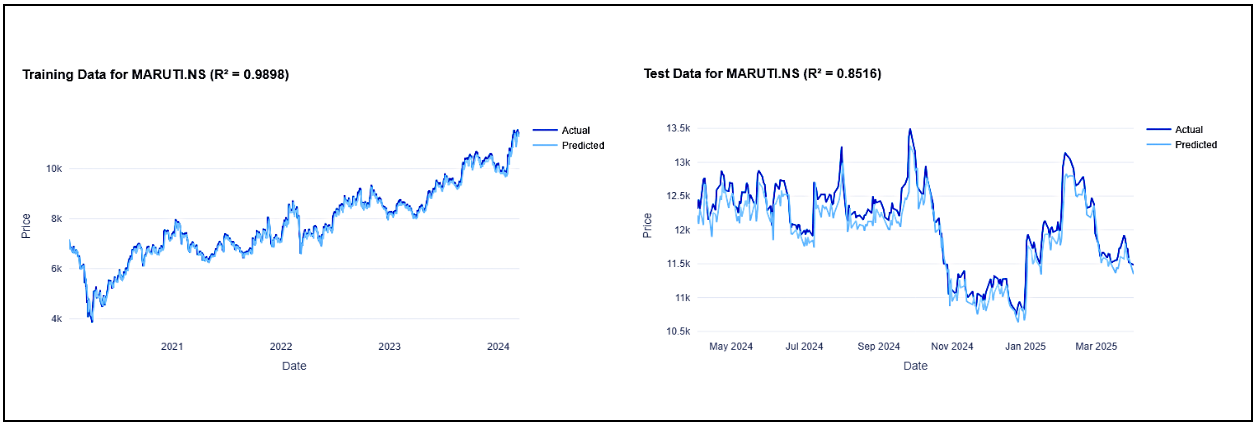

Figure 8 Maruti

Date	Predicted Close	Predicted High	Predicted Low
2025-04-03 00:00:00	11,647.0732	11,746.9229	11,550.7881
2025-04-04 00:00:00	11,476.7363	11,576.5859	11,380.4512
2025-04-07 00:00:00	11,319.1074	11,418.9570	11,222.8223
2025-04-08 00:00:00	11,181.9590	11,281.8086	11,085.6738
2025-04-09 00:00:00	11,066.5967	11,166.4463	10,970.3115

Maruti's predicted values exhibit a noticeable downward drift, warranting further investigation into sector-specific factors. The gradation between daily predicted highs and lows confirms the model's sensitivity to minor market corrections.

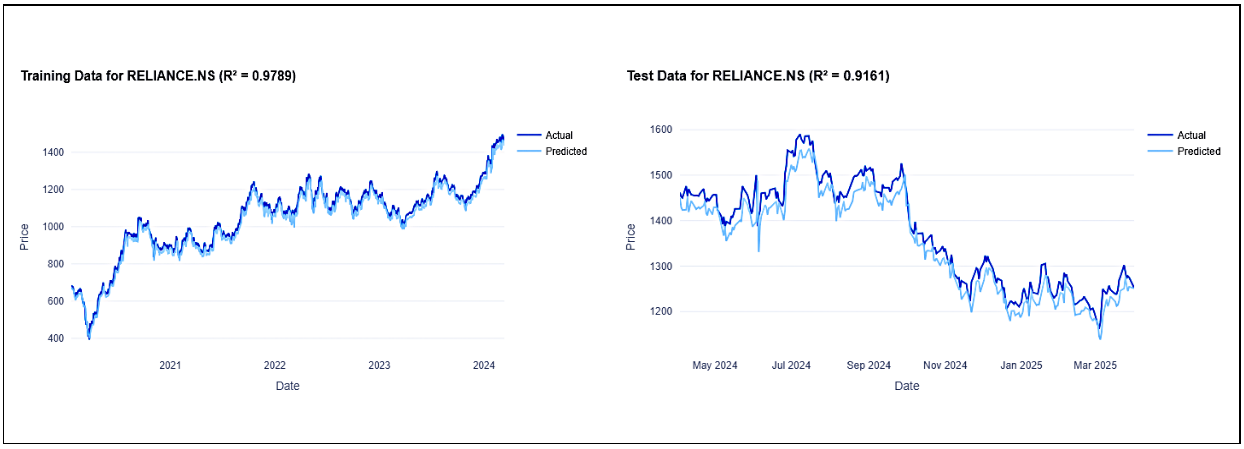

Figure 9 Reliance

Date	Predicted Close	Predicted High	Predicted Low
2025-04-03 00:00:00	1,226.7410	1,238.6801	1,215.8330
2025-04-04 00:00:00	1,202.3820	1,214.3210	1,191.4740
2025-04-07 00:00:00	1,176.8804	1,188.8195	1,165.9724
2025-04-08 00:00:00	1,153.5363	1,165.4753	1,142.6283
2025-04-09 00:00:00	1,131.1521	1,143.0912	1,120.2441

Reliance Industries' forecast features a modest decline with minimal deviation among predicted values. The close grouping reflects steady market conditions, lending confidence to the model's performance in a large-cap scenario.

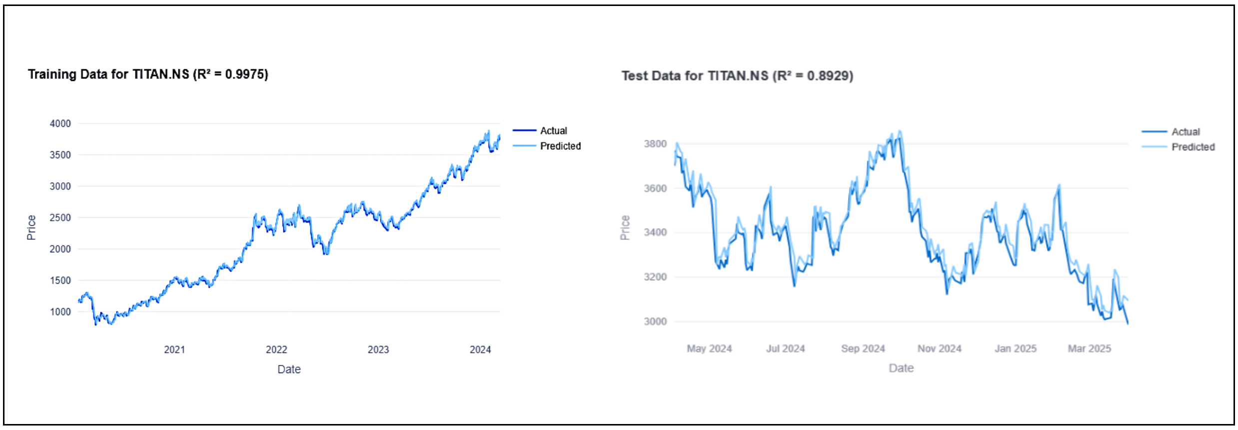

Figure 10 Titan

Date	Predicted Close	Predicted High	Predicted Low
2025-04-03 00:00:00	3,129.0159	3,156.3979	3,102.0813
2025-04-04 00:00:00	3,171.0107	3,198.3928	3,144.0762
2025-04-07 00:00:00	3,209.0923	3,236.4744	3,182.1577
2025-04-08 00:00:00	3,243.6448	3,271.0269	3,216.7102
2025-04-09 00:00:00	3,274.3196	3,301.7017	3,247.3850

Titan's output shows a gentle ascending trend, suggesting optimism in the consumer goods segment. The gradual increase across the predicted metrics aligns well with expectations of stable market growth.

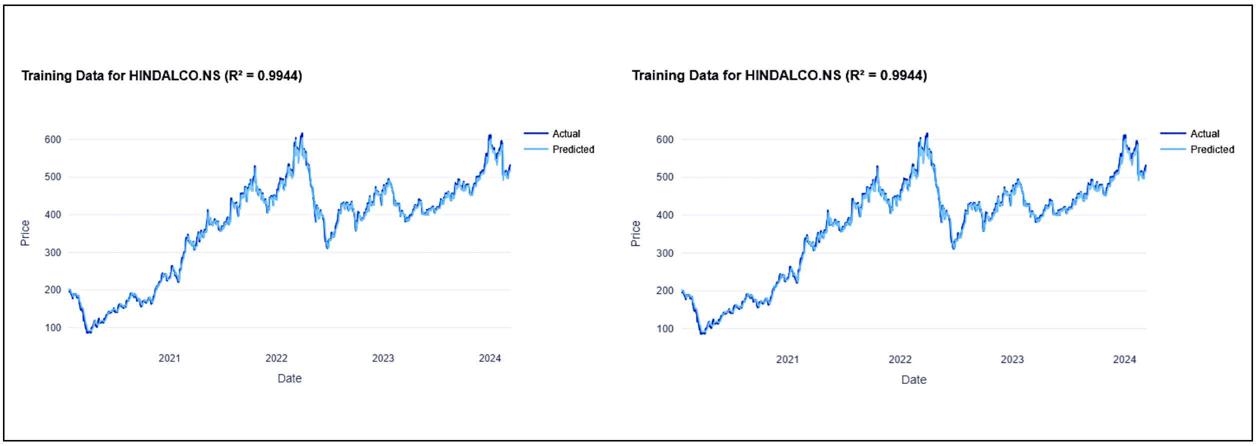

Figure 11 Hindalco

Date	Predicted Close	Predicted High	Predicted Low
2025-04-03 00:00:00	650.4773	656.8897	644.3684
2025-04-04 00:00:00	635.8770	642.2894	629.7681
2025-04-07 00:00:00	622.9313	629.3438	616.8224
2025-04-08 00:00:00	612.2169	618.6293	606.1080
2025-04-09 00:00:00	603.0596	609.4720	596.9507

In this alternative output for Hindalco, the predictions continue to display a downward trend, reinforcing the signal of cautious investor sentiment. The uniformity of the close, high, and low figures indicates that the model reliably tracks even small shifts in market behavior.

The resultant outputs such as photos, graphs, and tables of the outcomes are then enumerated towards the end of the research report to demonstrate the performance and usefulness of the whole analysis process.

VI. CONCLUSION

This research presents an inclusive stock market prediction system that combines various analyses, models, and indicators to deliver precise weekly forecasts. The model utilizes historical stock patterns and the upcoming trend with high precision. The given system uses machine learning models, technical indicators, sentiment analysis, and Long Short-Term Memory (LSTM) networks for time-series forecasting. There is a systematic approach given to the model to filter and identify stocks with high potential with profitable entry and exit points. To increase the efficiency, reliability, and precision, we have incorporated technical indicators such as the Volatility Index (VIX), RSI, Bollinger Bands, and GFS analysis known as multi-timeframe filtering strategy. Short-term stock movements play a significant role where sentiment analysis from financial news feeds further aid to strengthen the model by including market sentiment. The given strategical model is scalable and adaptable as this multi-timeframe structure helps the investors to gain huge profits in real time. Further, the model operates on a weekly prediction cycle that makes sure that the data utilized is the most recent market data collected. In conclusion, this research presents a hybrid computing model that predicts stocks weekly by combining LSTM, Multi-timeframe, technical analysis, and sentiment evaluation so that we can eliminate the manual computing and make an impeccable tool for common individuals, investors, risk mitigation, and maximizing profitability

VII. FUTURE WORKS

In future work, our project aims to add a few more features to improve accuracy and can be applied in real-time trading and the whole process can also be automated by clicking once. One more important key feature is adding alternative data sources, including social sentiment, economic indicators, and global financial news to provide a better accuracy than our project one more important plan to implement real-time trading and algorithmic execution enabling the model to function seamlessly within live trading platforms and support instant, data-driven investment decisions and the another plan is the automated model execution where in this module helps to search all the stocks in NSE index at once and gives the best performing set of stocks for the next week when this implemented all eliminating the need for manual intervention and ensuring timely weekly forecasts Additionally, the introduction of a dynamic stop-loss adjustment mechanism is also can be implemented in future this is very much useful to the traders because when the trader misses the stoploss signal this dynamic stop loss will automatically trigger the signal and ends the trading position and it can intelligently update stop-loss values in real-time as stock prices and reducing the losses for traders and finally we aim to continuously refine the system by advance AI and technological advancements like hybrid models, to improve adaptability and performance in volatile market conditions.

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