Stock Market Prediction Using Multi-Filtered LSTM Approach

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Abstract. This study introduces a hybrid framework for stock market prediction that combines key technical indicators—such as the Relative Strength Index (RSI), Volatility Bands (BB), and the Volatility Index (VIX)—with the Grandfather–Father–Son (GFS) trading strategy and Long Short Term Memory (LSTM) neural networks. The research focuses on 10 sectors of the Indian stock market, using historical price data sourced from Yahoo Finance to enhance real-time predictive accuracy. Technical indicators, the trading strategy, and web-scraped sentiment data—classified as positive, negative, or neutral—are collectively used to filter and refine the selection of sectors and their associated stock companies. The model architecture comprises a stacked LSTM with three hidden layers (32 units each) and one dense output node, trained using the Adam optimizer and mean squared error (MSE), and evaluated with an R^2 score. The goal is to implement technical and sentiment-based filtering with predictive modeling to outperform existing methodologies in accuracy, reliability, and efficiency, therefore reducing investor risk and maximizing returns.

Keywords: Stock Market Prediction · LSTM · Technical Indicators · Sentiment Analysis · Time Series Forecasting · Deep Learning · NSE · GFS Strategy

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 [1]. These challenges make market prediction extremely difficult but critically important for investors [2], [3]. In the context of Indian markets, research has identified unique characteristics such as high volatility and increased market participation [4], [5], [6]. Studies of indices like Nifty50 and SENSEX have helped investors understand these challenges and opportunities [6], [7]. The sensitivity of the market to domestic news as well as global trends further motivates the need for advanced predictive modeling [8].

Technical metrics from the indicators have a major role in identifying market trends and momentum. Such as the Relative Strength Index (RSI) and Bollinger Bands (BB) are critical for signaling trend reversals and potential entry or exit points [9], [10], [11]. Moreover, investors have progressively adopted hybrid systems that combine multiple indicators to generate sophisticated trading signals [12], [13], [14].

II LITERATURE SURVEY:

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 [11].

In this paper the author trying to find the Stock Price for NSE Using Advanced Deep Learning Methods The idea that is proposing is comparing deep learning techniques such as (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 well-suited for stock prediction because of its capability to learn localized patterns. [4]

III RELATED TERMINOLOGIES:

A Stock Technical Indicators (STIs):

These are mathematical tools derived from market price and volume data. They are not dependent on a financial fundamental such as earnings or sales margins. Technical analysts consider that "market behavior can be inferred from past trends and are generally driven by observed movements" or "trend-oriented analysis."

The commonly used technical indicators and their respective formulas utilized in this study are summarized in Table 1.

Table 1. Technical Indicator Formulas

Indicator	**Calculation**
SMA	$\frac{\sum_{i=1}^{n} \text{Close}_i}{n}$
Volatility Bands (BB)	$SMA \pm (k \times \sigma)$
RSI	$100 - \frac{100}{1+\frac{AG}{AL}}$
VIX	Market volatility index

B Trading Strategy:

GFS stands for Grandfather Father-Son. This is a multi-timeframe trading strategy that analyze 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.

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 listed in the NSE, India.

A Acquisition of Dataset:

The target is to analyse and identify strong-performing stocks by looking into all 10 sectors and the companies within those sectors we utilized Yahoo Finance APIs to obtain the stock datasets of the mentioned companies for our analysis for the last 5 years till today's date (2021 to 2025) using Company names are represented by ticker symbols, and the dataset features various attributes such as Open, High, Low, Close also known as (OHLC). We are primarily using the close price as the main input. In addition to estimating the closing price, we are also interested in forecasting the maximum and minimum prices reached by the companies during the trading day.

B Dataset Insights:

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 Benchmarking Metrics:

Root Mean Squared Deviation: This is the most commonly applied metric to measure the gap between predicted and actual outcomes. RMSD calculates the square root of the difference among observed and forecasted values.

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

R^2 Score: Determines how well the model's predictions fit the actual data.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2}$$

D Machine Learning Models:

NLP for web scraping and sentiment analysis: The 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 analyse 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.

Long-Short Term Memory: Our model utilizes an LSTM structure that excels at capturing temporal dependencies by selectively preserving relevant patterns across time steps. We selected LSTM because of its gated mechanism, which enhances control over data flow. Each of the three gates has its own functionality. Controlled by one gate, only certain information is added to memory cell. Another gate distinguishes what information must be removed from the memory cell. the output gate decides what data should be displayed as the output. In our study, the LSTM acts as a final prediction layer that learns trends from pre-filtered stock data. After the applying of technical indicators and sentiment screening, LSTM helps model time-based dependencies such as weekly closing prices by revealed its internal memory cells that adaptively store and retrieve context from previous trading intervals. We choose only LSTM among various deep learning architectures because of its strength in modeling time-dependent behavior, which is essential in stock market data. Unlike standard neural networks that handle each data point independently, LSTM captures long-term dependencies by retaining important historical patterns through its internal memory design.

V RESULTS & DISCUSSION:

Technical indicators like 14 days (RSI) and (BB) are calculated. These indicators measure how much stocks move up or down, and how strong that upward or trend force is. We analyze them daily, weekly, and monthly. The multi-time frame strategy covers all the key intervals.

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.

And then the software extracts news headlines from sources. This is the point where the determination is made of whether news sentiment towards a company is optimistic, critical, or unbiased. If the sentiment of a company is extremely negative, the company is excluded from further consideration.

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 coming day's company stock price. The model is trained with Adam-based optimizer and MSE, and after training, makes future price predictions along with a simple evaluation metric like R^2 scores for the train and test set.

As shown in Table 2, the proposed hybrid model (R^2: 0.96) performed better than Sharma et al.'s automotive sector-based dependency model [6] (R^2: 0.88) and Agrawal et al.'s LSTM-technical indicator-based model [8] (R^2: 0.85) on NSE data. As depicted in Figure 1, the HINDUNILVR stock shows improved performance, with predicted values closely aligned to actual values during both the training and testing phases. Hence, this indicates our model's potential in capturing both sectoral trends and sentiment influences.

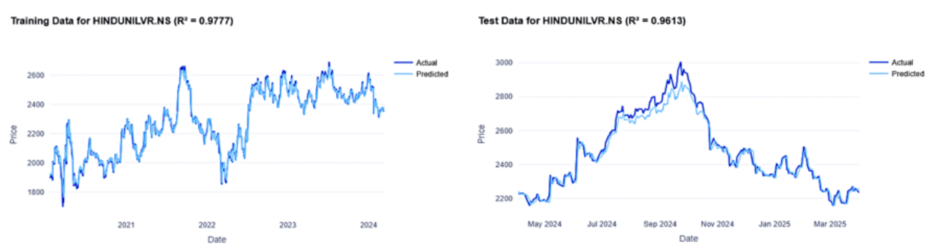

Fig. 1. Test vs Train prediction performance for HINDUNILVR stock

Table 2. Comparison of Proposed Model with Previous Works

Model	**Normalized RMSE**	$\mathbf{R^2}$	**Dataset**
Proposed	1.17%	0.96	NSE (2020 - Current)
Sharma et al. [6]	1.12%	0.88	Automotive
Agrawal et al. [8]	0.78%	0.85	S&P 500

VI CONCLUSION:

This research presents an systematic approach given to the model to filter and identify stocks with high potential with profitable entry and exit points. To enhance the overall accuracy and robustness of the system, we utilized a combination of technical tools, including the Volatility Index (VIX), Relative Strength

Index (RSI), and Bollinger Bands. These indicators were integrated alongside a multi-timeframe strategy (GFS) to refine stock selection and trend validation. 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.

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