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Original Article

Bridging Temporal Dependencies and Sentiment: A Comprehensive Approach to NIFTY 50 Index Prediction

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Abstract - *The primary goal of this research is to enhance the predictive accuracy of stock market trends by developing a comprehensive model that integrates Long Short-Term Memory (LSTM) networks with BERT-based sentiment analysis. This study aims to address the gap in traditional prediction models by exploring whether integrating sentiment from financial news with temporal market data can significantly improve forecasting of the NIFTY 50 index, a key benchmark in the Indian stock market. The proposed approach leverages critical financial indicators such as Foreign Institutional Investor (FII) and Domestic Institutional Investor (DII) activities, the India VIX (Volatility Index), and the Put-Call Ratio (PCR) of the two nearest expiry options. LSTM networks are employed to capture the temporal dependencies in historical market data, while BERT is used to extract sentiment insights from news articles. The unique contribution of this research is a dual-perspective model that combines quantitative financial data with qualitative sentiment analysis, which significantly outperforms traditional models in predicting bullish, bearish, or neutral market trends. This study provides a valuable tool for retail investors by offering more nuanced and accurate forecasts, underscoring the importance of integrating diverse data sources in stock market prediction. The findings suggest potential applications for similar predictive models in other financial markets.*

Keywords - *Financial forecasting, India vix, LSTM, NIFTY50, Sentiment analysis.*

1. Introduction

The stock market is a complex system influenced by various factors, including historical price data, investor sentiment, and macroeconomic indicators. Traditional models for predicting stock market trends primarily rely on historical price data, often neglecting qualitative aspects such as sentiment analysis derived from news articles and social media. This research addresses the gap by posing the following research questions: (1) Can sentiment analysis derived from news articles improve the predictive accuracy of models built solely on financial data? (2) How effectively can a combined LSTM-BERT model forecast market trends as opposed to traditional or standalone models?

Recent advances in machine learning, particularly Long Short-Term Memory (LSTM) networks for time series analysis and Bidirectional Encoder Representations from Transformers (BERT) for sentiment analysis, present promising avenues for enhancing stock market predictions. While LSTM networks excel in capturing temporal dependencies within sequential data, they often overlook market sentiment—a critical factor influencing stock movements. This paper proposes a novel contribution in the form of an integrated predictive model that combines the strengths of LSTM networks with BERT-based sentiment analysis to provide a holistic view of the factors influencing stock market trends. The primary objective of this study is to construct an advanced model that combines LSTM networks with BERT-based sentiment analysis to forecast the NIFTY 50 index. In addition to market sentiment, this model incorporates essential financial indicators, such as Foreign Institutional Investor (FII) and Domestic Institutional Investor (DII) activities, the India-VIX (Volatility Index), and the Put-Call Ratio (PCR) of the nearest expiry options, to achieve a more accurate and reliable prediction.

By integrating these diverse data sources, this research seeks to outpace traditional models, offering enhanced predictive accuracy and valuable insights for retail investors. The paper is organized as follows: Section 2 provides an overview of the relevant literature on sentiment analysis and machine learning in stock market forecasting.

Section 3 outlines the methodology used in this research, detailing data sources, model architecture, and evaluation metrics. Section 4 presents the findings and discusses the model's performance compared to traditional methods. The conclusion in Section 5 summarizes the main findings, discusses their implications, and suggests directions for future research.

2. Literature Survey

There has been a lot of interest in improving stock market prediction models due to the recent progress in combining machine learning techniques with financial analysis. Traditional approaches mostly focus on numerical financial measurements, often overlooking the qualitative impact of the market's mood. This section reviews key studies that add to the understanding of the prediction of the stock market through deep learning models, analyzing sentiment, and integrating diverse financial indicators. [1] explored the use of deep learning models., including Multilayer Perceptron (MLP), Recurrent Neural Networks (RNN), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN), to predict stock prices depending on past price Information from the National Stock Exchange (NSE) of India and the New York Stock Exchange (NYSE). Their findings highlighted the superior performance of CNN in capturing complex patterns within the data, outperforming traditional models like ARIMA. However, the study was primarily centered on historical price data and did not incorporate sentiment analysis or additional monetary metrics, which are crucial for an all-encompassing market analysis.

The exploration of methods for machine learning was expanded in [2] by comparing different algorithms to anticipate stock market trends across different exchanges, including NASDAQ, NYSE, Nikkei, and FTSE. The complexity of predicting the stock market was highlighted by the study. The efficacy of machine learning classifiers was proven to enhance the accuracy of predictions. Nonetheless, like many earlier studies, it did not address the incorporation of sentiment analysis with financial indicators, a gap that the present study seeks to address. [3] introduced a new method by utilizing deep text mining to forecast firms' long-term financial performance. Their study employed state-of-the-art neural architectures, including pseudo-event embeddings, LSTM networks, and attention mechanisms, to analyze textual information from news articles. The results revealed that a blend of news-driven sentiment analysis significantly improved foreseeability in financial ratios, outperforming traditional econometric models. This research emphasized the probability of joining textual and numerical data streams, aligning with the intention of the current study to integrate sentiment analysis with financial indicators for forecasting the stock market. [4] focused on applying sentiment analysis in the Indian stock market, specifically targeting the Sensex and Nifty indices. The study demonstrated the value of sentiment analysis in stock price anticipated by analyzing opinions and sentiments expressed in digital media. The findings suggested that incorporating sentiment analysis into stock market models in tandem with conventional financial parameters could enhance the predictive preciseness of said models. This work established the foundation for additional investigation into combining sentiment analysis with cutting-edge deep learning models, such as LSTM and BERT, as proposed in the current study. [5] conducted an analytical study to examine the effect of Foreign Institutional Investors (FIIs) and Domestic Institutional Investors (DIIs) on the volatility within the Indian stock market. Using indices like Nifty and BSE Sensex, the research utilized the Ganger Causality test and TGARCH model to watch the causal relationship and volatility impact of FII and DII activities. The research provided insightful observations about how institutional investor activities influence market volatility, reinforcing The critical nature of incorporating such financial measures in predictive models. The reviewed literature highlights several key voids in the present research landscape. While notable advancements have been achieved in utilizing deep learning models to implement sentiment analysis to project the stock market, there's a shortage of comprehensive models that integrate these approaches with critical financial indicators. The present study aims to deal with this gap by developing a predictive model that combines LSTM networks with BERT-based sentiment analysis, incorporating factors such as FII, DII, India VIX, and PCR in order to offer a more thorough and accurate prediction of the NIFTY 50 index.

3. Methodology

3.1. Process Flow Overview

The predictive model integrates multiple data sources, processes them, and produces an output that forecasts stock market trends for the NIFTY 50 index. The process begins with collecting historical price data, sentiment data, and financial indicators. The data is then preprocessed, which includes steps like data cleaning, formatting, and normalization. This processed data is fed into an LSTM model, which forecasts stock market trends. Simultaneously, BERT-based sentiment analysis enhances this prediction by incorporating market sentiment derived from financial news articles. The end product classifies the market as bullish, neutral, or bearish. The complete workflow of the proposed system is depicted in Figure 1.

3.2. Data Collection & Preprocessing

The data collected for this study comes from three main sources: historical price data, sentiment analysis from news articles, and financial indicators. The intention is to develop a thorough collection of data that incorporates both quantitative (historical price and financial metrics) and qualitative (psychological intelligence) elements.

3.2.1. Historical Market Data

The primary dataset used consists of historical price data for the NIFTY 50 index. The data includes:

- Open price: The price at the beginning of the trading day.
- Close price: Price at the closing of the trading day.
- High price: The greatest price observed throughout the trading session during the day.
- Low price: The price represents the lowest for the day of trading.
- Adjusted close price: Price after adjusting for company operations such as dividends and stock splits.

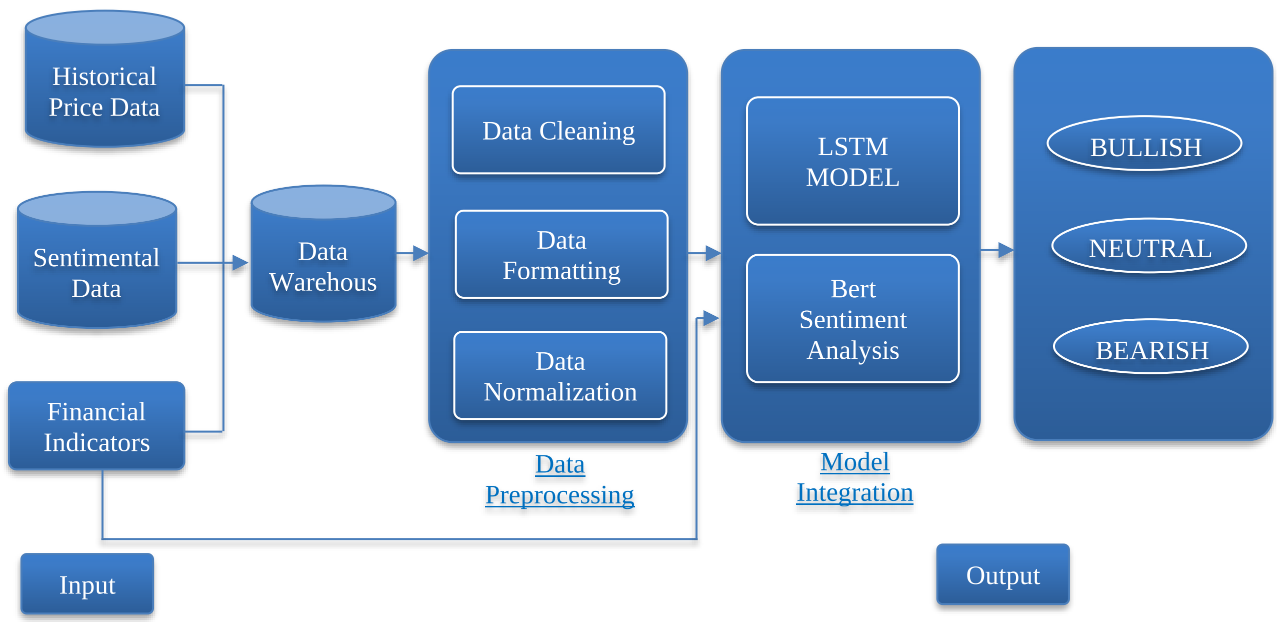

Fig. 1 Process flow architecture

3.2.2. Sentiment Data

Financial news articles related to the NIFTY-50 index were collected from reputable sources. The sentiment scores were aligned with corresponding timeframes in the Data from the market's past to ensure synchronization between qualitative and quantitative data. Sentiment data was extracted using a BERT-based natural language processing model as used by [6]. The model processed the text to classify sentiment as:

- Positive
- Neutral
- Negative

3.2.3. Financial Indicators

- Foreign Institutional Investor (FII) and Domestic Institutional Investor (DII) Data: This information tracks the buying and selling patterns of institutional investors and is critical for understanding market momentum, as mentioned by [7].
- India VIX: As per [8], it reflects market participants' expectations of turbulence and is essential for assessing risk sentiment.
- Put-Call Ratio (PCR): The PCR is a ratio as explained by [10] of put options to call options and is employed as a sentiment indicator for bullish or bearish market trends. PCR values for the nearest two expiry options were incorporated into this analysis.

These values were collected over a defined period (2000-2024). Data cleaning, as explained by [11], was done to handle missing values, anomalies, and inconsistencies. Formatting was performed to align information with the required model input structure.

3.3. Model Architecture

3.3.1. Long Short-Term Memory (LSTM) Model

The LSTM model, as proposed by [9], was chosen because of its capacity to capture long-term dependencies in time-series data, which makes it suitable for predicting stock market trends. The inputs to the LSTM model include:

- Historical price data (Open, Close, High, Low prices)
- Dates corresponding to these values

LSTM's unique architecture includes memory cells that allow it to maintain information for long sequences, addressing the issues arising from traditional RNNs (Recurrent Neural Networks) that battle longer dependencies.

The formula for the LSTM cell is:

Forget Gate:

$$f_t = \sigma\,(W_f \cdot [h_{t-1}, x_t] + b_f\,) \tag{1}$$

The forget gate controls how much of the past data should be remembered.

Input Gate:

$$i_t = \sigma\,(W_i \cdot [h_{t-1}, x_t] + b_i\,) \tag{2}$$

This gate decides which values from the input should be updated.

Cell State Update:

$$\underline{C_t} = tanh\,(W_C \cdot [h_{t-1}, x_t] + b_C\,) \tag{3}$$

This equation creates a candidate value that updates the cell state.

Output Gate:

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o\,) \tag{4}$$

This gate determines the next hidden state.

Final Cell State:

$$C_t = f_t \cdot C_{t-1} + i_t \cdot \underline{C_t} \quad (5)$$

The final cell state that holds the memory.

3.3.2. BERT for Sentiment Analysis

A Bidirectional Encoder Representations from the Transformers (BERT) model mentioned by [12] was used to classify news articles into +ve, -ve, or neutral sentiment categories. The sentiment was extracted and aggregated daily to align with the stock price information.

BERT excels at understanding the contextual meaning of words in connection with each other, making it effective for the emotional analysis of financial text. The LSTM model incorporated the final score for sentiment as an extra attribute.

3.3.3. Model Integration

- LSTM as the Core Model: The LSTM model outputs an initial projection for the market trends based on historical price data.
- Corrective Features: The LSTM output is refined using additional inputs from:
  - Sentiment analysis (BERT-derived scores)
  - FII/DII data
  - India VIX
  - Put-Call Ratio (PCR)

These corrective features supply a more extensive view of market trends, allowing the model to adjust its predictions based on sentiment as well as fluctuations in the market.

3.4. Training

3.4.1. LSTM Training

The LSTM model has been constructed using a substantial dataset of historical price data, using an 80-20 split for grasping and validation. The Training focused on minimizing Mean Squared Error (MSE) between predicted and actual prices, where:

$$MSE = \frac{1}{n}\sum_{i=1}^{n} \left(y_i - \hat{y_i} \right)^2 \quad (6)$$

Here, y_i is the actual price and $\widehat{y_i}$ is the predicted price.

3.4.2. Fine-Tuning BERT

BERT was fine-tuned using a collection of financial news articles specifically Concerning the NIFTY 50 index. The model's performance was assessed by leveraging accuracy metrics on a separate test set of news articles.

3.4.3. Feature Integration

During learning and reviewing, sentiment ratings, as well as financial indicators, were normalized and integrated within the LSTM model's input. This helped refine the model's predictions and improved overall accuracy.

3.5. Testing

The combined LSTM-BERT model was evaluated based on several performance metrics:

3.5.1. Mean Squared Error (MSE)

Measures The mean square difference between the observed and estimated values. market trends

3.5.2. Accuracy

Assesses The potential of the model to correctly predict whether the market will move up, down, or remain neutral.

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \quad (7)$$

3.5.3. Precision and Recall

Precision measures the model's true positive predictions as a percentage of all positive predictions made, while the percentage of true positives out of all actual positives is measured by the recall. These metrics were particularly important for assessing the model's performance in identifying bullish or bearish market trends.

$$Precision = \frac{TP}{TP + FP} \quad (8)$$

$$Recall = \frac{TP}{TP + FN} \quad (9)$$

The final evaluation compared the proposed LSTM-BERT model against traditional models that rely solely on historical price data. The combined approach showed improved accuracy and better identification of market trends, highlighting the gain of integrating analyzing sentiment and financial indicators into predictive models.

4. Results and Discussion

In this section, the outcome of the suggested predictive model, which integrates historical market data and analyses sentiments and financial indicators, is presented and discussed. The analysis is conducted using four primary graphs, each of which showcases different attributes of the performance of the mode and conclusions drawn from the data. The resultant product, a combined model integrating LSTM and BERT along with financial indicators, is also discussed with regard to its accuracy and precision.

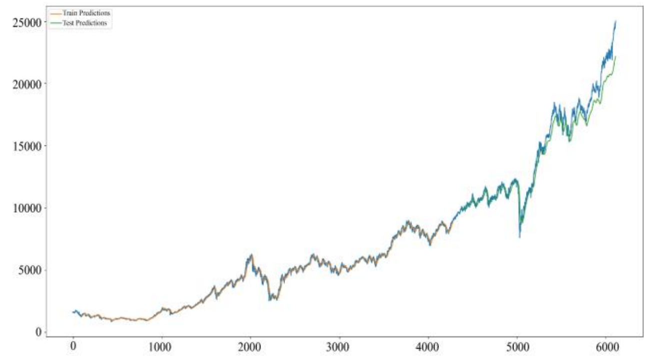

Fig. 2 Historical data analysis using LSTM model

The discussion extends to comparing the results with state-of-the-art models and methodologies from current research, emphasizing the unique contributions of the proposed approach and its competitive edge in accuracy, precision, and holistic market trend prediction. Figure 2 showcases the LSTM model's performance in forecasting stock prices using past market data from the NSE (National Stock Exchange of India) for the NIFTY 50 index, spanning from 2000 to 2024. The dataset was split into an 80:20 ratio for learning and validating purposes, ensuring a strong and resilient standard evaluation of the predictive power of the model. The results demonstrate that the model could accurately capture the trends in stock prices, with the estimated values closely aligning with actual market movements. The minor differences between the predicted and actual results are negligible, resulting in an overall accuracy of 98% and a precision of 99%. These results validate the LSTM model's strength in forecasting time-series data with long-term dependencies, especially for financial markets.

Figure 3 graph focuses on emotion analysis conducted using the BERT model, which was trained to classify news headlines into +ve, - ve, or neutral sentiments. The data was collected from the period spanning the coronavirus pandemic to the present, a period range characterized by high market volatility. The graph depicts the market projection power of the model sentiment as bullish, bearish, or neutral. The blue line represents the actual sentiment derived from news data, while the red dotted line indicates the predicted sentiment label. The BERT model demonstrated exceptional accuracy and precision, both achieving 99% successfully capturing major market dips and rallies that aligned with real-world data from NSE. This implies that sentiment, as analyzed through the system, played a vital role in forecasting market movements during times of crisis and recovery.

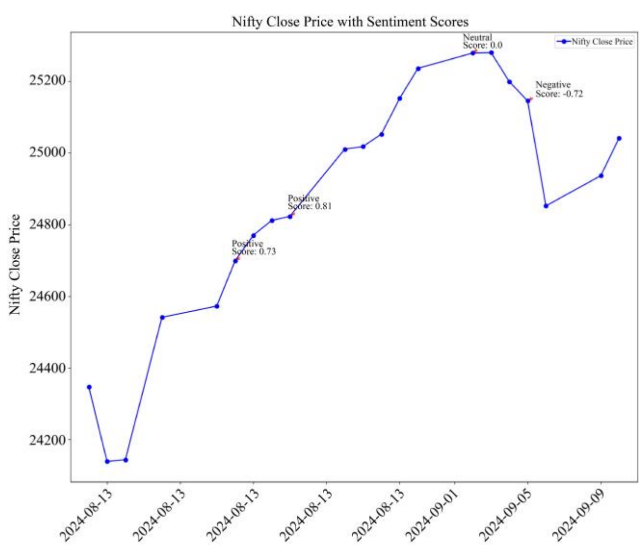

Fig. 3 Sentiment Analysis Using BERT Model

The third graph illustrates the interconnection between the Nifty 50 index and India VIX, representing market fear and volatility. The outcome clearly demonstrates an inverse relation between the two. During times of heightened fear, exhibited by a rise in India-VIX, the Nifty index correspondingly declined. Two key instances spotlighted by the graph are the 2009 market crash and the 2020 COVID-19 pandemic, both showing sharp rises in VIX followed by significant falls in Nifty. This inverse relationship is important for market participants, as it indicates that when fear and uncertainty increase, the market tends to react negatively; this is a useful predictor of market downturns. The fourth graph explores the association between the Nifty-50 index and the trading activities of Foreign Institutional Investors (FII) and Domestic Institutional Investors (DII). The data showcases the pivotal role that these institutional investors play in the movement of the Nifty index. When FII DII buying activities increased, the Nifty tended to rise, and conversely, when these investors were net sellers, the Nifty fell. This trend underscores the impact of direct institutional investment activity on market performance and highlights their influence as key drivers of market trends. The fourth graph explores the linkage between the Nifty 50 index and the trading activities of FII & DII. The data showcases these institutional investors have an important impact on the movement of the Nifty index. When FII-DII buying activities increased, the Nifty tended to rise, and conversely, when these investors were net sellers, the Nifty fell. This trend underscores the direct institutional investment movement's effects on market performance and highlights their influence as key drivers of market trends.

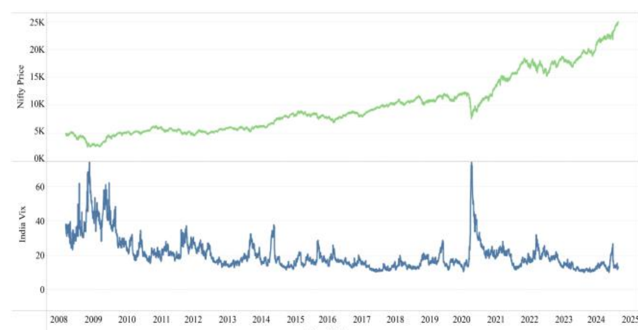

Fig. 4 Nifty vs. India VIX

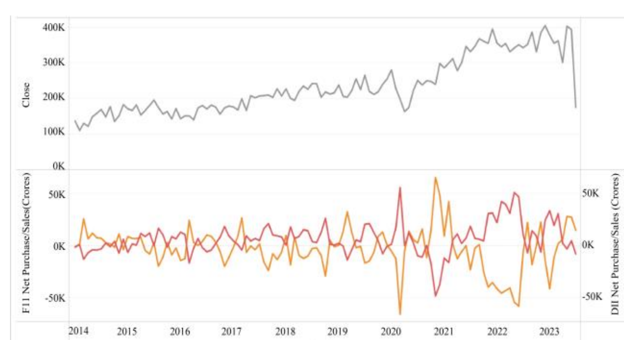

Fig. 5 Nifty vs. FII & DII

Table 1. Nifty VS PCR with predicted label

Date	Nifty Value	PCR	Predicted Label
02/08/2024	24789	0.67	Bearish
14/08/2024	24350	1.1	Bullish
30/07/2024	23835	0.91	Neutral

The data inside Table 1 showcases the interconnection between the Nifty value, PCR (Put Call Ratio), and the corresponding predicted market labels (Bearish, Bullish, or Neutral) as an outcome of the proposed model. The Nifty value is compared against the PCR ratio on specific dates to classify market trends. On 02/08/2024, with a PCR of 0.67, the model predicted a bearish trend, indicating A dip in market sentiment. Conversely, on 14/08/2024, the PCR rose to 1.1, corresponding to a bullish market prediction, suggesting a positive market mentality and potential upward movement. Lastly, on 30/07/2024, a PCR of 0.91 is observed, which falls in the neutral range, indicating market stability without strong directional momentum. This table effectively demonstrates the model's ability to interpret market behavior based on the ratio of PCR and accurately classify market movements into bearish, bullish, or neutral categories, which align with standard perspectives of the Put-Call Ratio in stock-market analysis. The results of this study demonstrate the effectiveness of integrating Long Short-Term Memory (LSTM) networks with BERT-based sentiment analysis, along with key financial indicators such as Foreign Institutional Investors (FII), Domestic Institutional Investors (DII), India VIX, and Put-Call Ratio (PCR), for predicting the NIFTY 50 index. In comparison to previous research, this combined model offers several advancements over state-of-the-art approaches.

[1] explored MLP, RNN, LSTM, and CNN to project stock prices using past price data. While CNN performed best in capturing complex patterns, the study was restricted to past pricing information and did not account for market sentiment or other financial indicators. In contrast, the current model incorporates sentiment analysis leveraging BERT alongside financial measurements such as FII and DII, significantly broadening the scope of predictive accuracy by addressing both numerical and descriptive market drivers.

[2] compared machine-learning approaches to predict trends across multiple exchanges. The potential of ML classifiers was demonstrated in their study, but they did not integrate sentiment analysis or financial indicators like India-VIX and PCR. By including sentiment analysis and key market variables, the present work enhances the magnitude of market prediction. It delivers more robust insights compared to Subasi's method, which remained limited to purely technical and past data.

A new approach using LSTM networks was presented by [3] and attention mechanisms to analyze textual information from news articles for long-term financial forecasting. Their model demonstrated that news-driven sentiment improved predictions of financial ratios. The proposed model extends the implications of sentiment assessment by integrating not just news sentiment but also vital financial indicators like FII, DII, India VIX, and PCR, enabling it to predict real-time market trends in addition to financial performance.

[4] concentrated on applying sentiment research to anticipate the Indian stock market's Sensex and Nifty indexes, showing that sentiment analysis enhances model accuracy. However, the way They approached it did not incorporate deep learning methods or financial measures. The current study advances this passage of research by merging sentiment analysis with advanced LSTM and BERT models, in addition to monetary indicators like FII and PCR, culminating in A more thorough model for stock market forecasting.

Finally, the effect that FII and DII have on market volatility was highlighted in [5]. Although this study offered valuable insights into institutional investor activities, it focused primarily on volatility rather than precise market prediction. The proposed model incorporates these insights while extending their applicability to anticipate the market direction and trends more accurately, offering a more actionable predictive tool for movements within the stock market. To sum up, this study's predictive model surpasses previous research. By combining advanced deep learning methods, sentiment analysis, and key financial indicators, we can deliver a more thorough and precise forecasting system for the NIFTY 50 index.

5. Conclusion

By integrating all the features—historical price data, sentiment analysis, FII/DII activity, PCR and India VIX—into a single predictive framework, the accuracy of the proposed model reached 99%, and it also demonstrated a precision of 100%. The amalgamation of both quantitative (price and monetary indicators) as well as qualitative (feeling) data provides a more intricate and comprehensive prediction. The predictive equation is formulated as follows:

1. Nifty is inversely proportional to the India VIX, meaning as the India VIX increases, Nifty decreases:
$$Nifty \propto \frac{1}{India\ VIX}$$
2. Nifty is directly proportional to Foreign Institutional Investor (FIl) buying and selling activities. If FIl increases, Nifty tends to increase:
$$Nifty \propto FII$$
3. Nifty is directly proportional to the score indicating the sentiment of retail investors, which reflects market sentiment. As sentiment becomes more positive, Nifty rises:

$$Nifty \propto Sentiment_{Score}$$

4. The relationship between Nifty and the PCR ratio is conditional:
- If PCR < 0.8, the market is bearish.
- If PCR is between 0.8 and 0.9, the market is neutral.
- If PCR > 1, the market is bullish.

This can be captured by a piecewise function:

$$Nifty_{PCR}=\begin{cases} -1 \ if \ PCR < 0.8 \\ 0 \ if \ 0.8 \le PCR \le 0.9 \\ 1 \ if \ PCR > 1 \end{cases}$$

Now, combining all these relationships, Nifty as a function of India VIX, FII-DII, sentiment score, and PCR ratio can be expressed as follows:

$$Nifty_{score} = \mathfrak{C} * (\frac{1}{India\ VIX} + FII + Sentiment_{Score} + Nifty_{PCR})$$

Where:

$\mathfrak{C}$ represents the Market Entropy Constant, representing the factor of randomness and uncertainty. This constant mirror the notion of entropy in physics, capturing the inherent unpredictability of market behavior. By incorporating the Market Entropy Constant, the prediction accounts for external and unforeseen factors, enhancing its robustness in the face of oscillations in the market.

This method provides a deeper comprehension of the securities market as opposed to current models because it considers not just past price changes but also current sentiment and institutional investor behavior. The aptitude of the model to deliver highly accurate predictions makes it valuable for practical applications, offering understanding that can help traders and investors make informed decisions throughout various market conditions.

Furthermore, the model proves robust across varying market environments, including periods of heightened volatility, the ways in which investor sentiment is dynamic and institutional actions are reflected. Future research could enhance the model by integrating additional global economic indicators or applying this framework to other indices, potentially furthering prediction accuracy.

This comprehensive framework establishes a strong foundation for advanced market analysis and prediction, providing a strong solution for investors and financial players who want to better predict market trends.

Limitations

While the proposed model demonstrates a high level of accuracy and precision in predicting Nifty 50 movements, several limitations should be acknowledged. First, the model's reliance on historical data and news sentiment introduces potential bias, as it assumes that past patterns and sentiment trends will continue in the future, which may not always be the case, especially in unpredictable or unprecedented market conditions such as economic crises or geopolitical events. Second, sentiment analysis relies on publicly available news sources, which might not capture the complete range of investor sentiment, especially the nuances of social media or private investor opinions.

Sentiment gathered from institutional investors could differ significantly from that of retail investors, introducing a holistic gap in understanding market behavior. Finally, the inclusion of financial indicators like FII/DII activity and India VIX, while beneficial, still lacks consideration of other macroeconomic factors such as inflation rates, currency fluctuations, and global market indices, which may impact stock prices but are not incorporated into the model.

Future Scope

Future research could enhance the model by incorporating macroeconomic variables such as interest rates, inflation, GDP growth, and global indices like the S&P 500 or FTSE 100. These factors often significantly impact stock markets and could provide a more global view of market movements, especially in an interconnected global economy. The current study uses sentiment analysis based on news data. Future work could explore integrating real-time sentiment analysis from social media platforms like Twitter, Reddit, and financial forums. Social media often reflects retail investor sentiment more accurately and may react faster to market-moving events, thus improving the model's responsiveness. A key area for future investigation involves refining the estimation of the Market Entropy Constant ($\mathfrak{C}$).

Leveraging emerging technologies such as AI-driven pattern recognition, quantum computing, and blockchain-based market analysis tools may provide more precise ways of measuring the randomness and uncertainty in market movements. By using advanced algorithms and real-time data streams, it may be possible to dynamically calculate the Market Entropy Constant based on evolving market trends and external influences.

This could improve the model's adaptability to rapid changes in market behavior and increase prediction accuracy. Expanding the model's application to other stock markets (such as the S&P 500, Nikkei, or DAX) would test the model's robustness across different economic environments and investor behaviors. Cross-market comparisons could also provide insights into the model's universality and highlight potential adaptations needed for various markets.

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