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News Sentiment Analysis in Financial Markets: A Survey

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***Abstract*—In recent years, the integration of sentiment analysis into financial markets has gained considerable attention, particularly through the use of machine learning and deep learning techniques. This survey explores the progress and challenges in applying these models to analyze news sentiment and its impact on market behavior. The work describes a comparison of recent deep learning architectures, such as Long Short-Term Memory, Convolutional Neural Networks, and hybrids in comparison to more traditional approaches of machine learning such as Support Vector Machines and Random Forest. The experiments indicated that the deep learning technique generally performed better than those conventional techniques, particularly where the model used a pre-trained language model. This work offers a comprehensive overview of the current state of development in financial news sentiment analysis and points out areas for further research in making models more robust and accurate.**

***Index Terms*—News, Sentiment Analysis, Financial Market**

I. Introduction

A variety of elements exert considerable influence on the financial markets; however, news and information play a pivotal role in shaping investor sentiment and market behavior. The overwhelming volume of financial news generated by the expansion of digital media poses challenges for investors, making it arduous to assimilate and utilize such information effectively in order to make informed decisions. In this context, the methodology of sentiment analysis would be highly critical, wherein it could be used to derive meaning from textual information and also applicable in risk assessment and market forecasting. Sentiment analysis refers to the concept of sentiments and opinions extracted from content written in words and initially proposed by Pang and Lee in 2008 [1]. Sentiment analysis has, over the years, grown to become an important tool with significant use in gauging public sentiment within financial markets with the rapid growth of data on the internet and AI plus NLP. The adoption of deep bidirectional transformers for language understanding through innovation such as BERT has significantly improved sentiment analysis. This study deals with the scrutiny of news sentiment in the realm of the stock market. It is a complex, constantly changing domain characterized by unique potentials and limitations. This paper provides an elaborate evaluation of methodologies for sentiment analysis, discusses their impact both on investors and regulatory authorities, and evaluates their potential in reflecting market sentiment with the synthesis of findings from several research studies. The structure of the manuscript is as follows: Section II presents a critical examination of the context of sentiment analysis, the limitations and implications in various domains. A major review of past literature is conducted in Section III: advanced natural language processing techniques in conjunction with the more typical machine learning methods. Section IV suggests avenues for future research-work that addresses current challenges, and forward-looking solutions. In conclusion, this rapidly advancing field is summarized in Section V by reviewing its most significant findings.

II. Background

Financial sentiment analysis has become the most important technique for predictive purposes in stock market movements, especially in an environment where social media, organizations dealing with financial news and online forums play a larger role in the decision process of investors. From analysing sentiments expressed in any textual information, including social media postings, news, and financial documents, experts provide analysts and traders deeper insights into market trends as well as investor behaviour. Way back, sentiment analysis rested mainly on traditional machine learning approaches. However, more complex deep learning architectures, such as LSTM networks and GRUs, presented a significant improvement, as shown by Erkut Memis et al [2] . The architectures are particularly good at detecting temporal patterns in financial datasets, outperforming traditional methods. Transformer-based models, such as BERT and its variant in finance, FinBERT, opened new avenues for sentiment analysis over the last few years, as shown by Roumeliotis et al. in 2024 [3]. These models show significant effectiveness in explaining complex linguistic structures and subtle sentiment differences, which are crucial for making well-informed decisions in volatile financial settings. The integration of sentiment analysis into algorithmic trading and risk management strategies has been proven to improve predictive power and general performance, as shown by Gaurav Sharma et al. in 2024 [4]. Such improvements give traders a competitive advantage in the execution of more informed and strategic investment decisions.

A. Challenges and Limitations of News Sentiment Analysis

Understanding the tone in financial news is hard and can lead to mistakes. One big problem is spotting sarcasm, irony, and small language details. Financial news often uses tricky words and terms specific to certain industries, which can confuse tools that analyse tone. For instance, a statement that sounds negative might actually just be careful, not pessimistic, and this can cause the tools to get it wrong. This issue gets worse because language varies across different financial fields and regions, making it harder to figure out the tone. Another major problem is that these tools rely on training data. If the data has biases, it can affect how well the tools work, especially in new or different financial situations, making them less accurate and useful. Additionally, financial markets change quickly, which means sentiment analysis models need regular updates to stay in line with new trends and terms. If these models aren't adjusted fast enough, they can produce outdated or incorrect predictions. Financial news comes in many forms, like formal articles or informal social media posts, making the task even harder. Variations in tone, writing style, and language across these sources create inconsistencies that models must handle. To tackle these issues, continuous research is crucial to build smarter models that can understand context better and adapt to the ever-changing world of financial communication.

B. Stock Prices Movement Due to News

Whether true or false, news has a great impact on financial markets. One recent incident came to light after Elon Musk bought X (formerly known as Twitter), when a user had bought a blue tick for just 8 dollars. The user created a phishing account under the name of Eli Lilly, which happens to be one of the biggest insulin manufacturers and sellers in the United States. The fraudulent announcement proclaimed that insulin would henceforth be free. Compounded by the challenge of distinguishing between authentic and counterfeit accounts at a cursory glance, this deceptive news swiftly disseminated through various news outlets without thorough cross-verification.

The consequences were swift and severe. Eli Lilly's stock price plummeted by 4.37 percent following the spurious tweet, as shown in Fig.**??**, resulting in the obliteration of billions of dollars in market capitalization. This vivid example underscores the formidable influence of news sentiment on financial markets, where a singular news event can exert a disproportionately substantial impact on the valuation of a financial instrument.

Adverse reactions in stock prices to negative news are common in the Indian Stock Market as well. On 31 January 2024, the Reserve Bank of India, which is the central banking authority and financial regulator of the nation, placed Paytm Payments Bank under restrictions. The bank asked it to stop taking new clients from then onward, and after that, put deposits in a suspension state. This announcement had a critical negative effect, leading to a sharp 45% fall in the company's stock value within just a few days, as can be seen in image II-A. This occurrence underscores the substantial impact that news sentiment exerts on market dynamics. It represents one of numerous instances in which news, irrespective of its veracity, has induced considerable fluctuations in the worth of financial instruments. These events emphasize the pressing necessity for mechanisms capable of effectively evaluating and mitigating the repercussions of news on market equilibrium and investor confidence.

C. Impact of news/events on stock indicies

Investors track the financial news because it is one of the major determinants of market sentiment. Major events tend to have sharp reactions in the stock market, and benchmark indices experience significant volatility after important announcements. To give an idea of how significant such events are, we have collected information from reliable sources such as Wikipedia and the Financial Express to prepare a detailed table.

The chosen benchmark index for this analysis is NIFTY 50[1], comprising the top 50 companies in India based on market capitalization. This index serves as a reliable indicator of the overall market performance. The table we present showcases the percentage change in the NIFTY 50 on the day of specific events, offering a clear illustration of the market's reaction to noteworthy occurrences. The data for the table I has taken from Wikipedia and Financial Expresses.

III. Methods and Approaches

In this section, we categorize the techniques used in News Sentiment Analysis into two main groups: Deep Learning Models and Machine Learning Models. Deep Learning Models include CNN, BERT, and LSTM, while Machine Learning Models cover methods like KNN, as shown in Fig. 5. Deep Learning models are further divided into CNN, BERT, and LSTM, while the Machine Learning category is represented by ELR-ML and KNN models. This division highlights the varying levels of complexity and learning mechanisms involved in financial sentiment analysis.

A. Machine Learning Models for Financial Sentiment Analysis

Machine Learning (ML) models such as K-Nearest Neighbors (KNN), Support Vector Machines (SVM), and Random Forest (RF) have been commonly applied to financial sentiment analysis due to their simplicity and interpretability.

[1]https://www.nseindia.com/market-data/live-equity-market?symbol=NIFTY%2050

Fig. 1. Tweet by the fake account

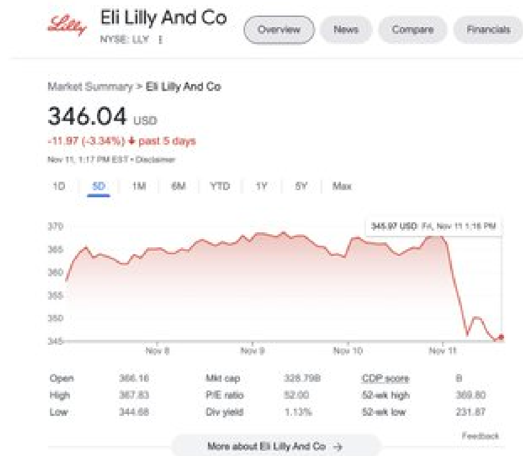
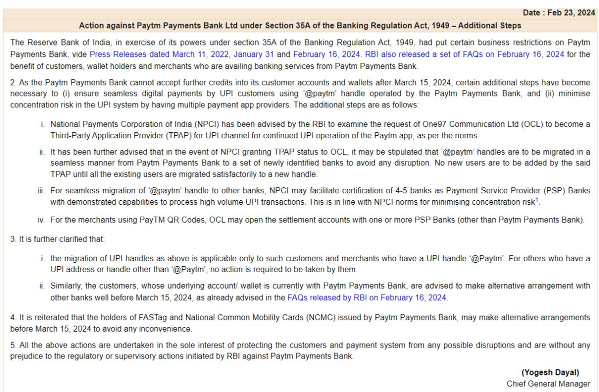


Fig. 2. Stock price reaction



Date : Feb 23, 2024

Action against Paytm Payments Bank Ltd under Section 35A of the Banking Regulation Act, 1949 – Additional Steps

The Reserve Bank of India, in exercise of its powers under section 35A of the Banking Regulation Act, 1949, had put certain business restrictions on Paytm Payments Bank, vide Press Releases dated March 11, 2022, January 31 and February 16, 2024. RBI also released a set of FAQs on February 16, 2024 for the benefit of customers, wallet holders and merchants who are availing banking services from Paytm Payments Bank.

2. As the Paytm Payments Bank cannot accept further credits into its customer accounts and wallets after March 15, 2024, certain additional steps have become necessary to (i) ensure seamless digital payments by UPI customers using '@paytm' handle operated by the Paytm Payments Bank, and (ii) minimise concentration risk in the UPI system by having multiple payment app providers. The additional steps are as follows:

i. National Payments Corporation of India (NPCI) has been advised by the RBI to examine the request of One97 Communication Ltd (OCL) to become a Third-Party Application Provider (TPAP) for UPI channel for continued UPI operation of the Paytm app, as per the norms.

ii. It has been further advised that in the event of NPCI granting TPAP status to OCL, it may be stipulated that '@paytm' handles are to be migrated in a seamless manner from Paytm Payments Bank to a set of newly identified banks to avoid any disruption. No new users are to be added by the said TPAP until all the existing users are migrated satisfactorily to a new handle.

iii. For seamless migration of '@paytm' handle to other banks, NPCI may facilitate certification of 4-5 banks as Payment Service Provider (PSP) Banks with demonstrated capabilities to process high volume UPI transactions. This is in line with NPCI norms for minimising concentration risk[1].

iv. For the merchants using PayTM QR Codes, OCL may open the settlement accounts with one or more PSP Banks (other than Paytm Payments Bank).

3. It is further clarified that:

i. the migration of UPI handles as above is applicable only to such customers and merchants who have a UPI handle '@Paytm'. For others who have a UPI address or handle other than '@Paytm', no action is required to be taken by them.

ii. Similarly, the customers, whose underlying account/ wallet is currently with Paytm Payments Bank, are advised to make alternative arrangement with other banks well before March 15, 2024, as already advised in the FAQs released by RBI on February 16, 2024.

4. It is reiterated that the holders of FASTag and National Common Mobility Cards (NCMC) issued by Paytm Payments Bank, may make alternative arrangements before March 15, 2024 to avoid any inconvenience.

5. All the above actions are undertaken in the sole interest of protecting the customers and payment system from any possible disruptions and are without any prejudice to the regulatory or supervisory actions initiated by RBI against Paytm Payments Bank.

(Yogesh Dayal)
Chief General Manager

Fig. 3. RBI action on Paytm

Fig. 4. Stock reaction

TABLE I
IMPACT OF GLOBAL EVENTS ON NIFTY 50

No.	Date	Event	NIFTY 50 Change
1	24 June, 2016	Brexit	-181.85 (-2.20%)
2	11 November, 2016	Demonetisation & US Election	-229.45 (-2.69%)
3	20 May, 2019	Lok Sabha Exit Poll	421.10 (3.69%)
4	23 May, 2019	General Election	300.90 (2.49%)
5	20 September, 2019	Corporate Tax Cut	655.45 (6.12%)
6	23 September, 2019	Corporate Tax Cut	420.65 (3.73%)
7	12 March, 2020	WHO Declared Pandemic	-868.25 (-8.25%)
8	23 March, 2020	COVID-19 Intensification	-1135.20 (-12.68%)
9	7 April, 2020	Peak COVID-19	708.40 (8.76%)
10	1 February, 2021	Positive Budget	646.60 (4.74%)
11	24 February, 2022	Russia-Ukraine War	-815 (-4.8%)

These models work well when applied to structured datasets like financial news headlines or stock prices. While ML models may lack the depth of representation found in deep learning approaches, they still offer valuable insights, especially for smaller datasets or less complex tasks. Table II summarizes various ML models and their effectiveness in

Author(s)	Model(s) Used	Dataset	Results
R. Srusti [5]	KNN	Financial headlines	Custom k-NN classifier achieved 82.67% accuracy, highlighted by confusion matrix relationships between sentiment classes.
Popoola et al. [6]	Random Forest, Naïve Bayes, KNN	Financial news tweets	Sentiment analysis showed mostly positive public sentiment toward financial news.
Margaret Sangeetha et al. [7]	Yahoo finance price index dataset.	Machine Learning (ELR-ML)	The ELR-ML model improved stock price forecast accuracy with better reliability.
Khandelwal et al. [8]	KNN, SVM, Linear Regression, Random Forest	73,762 tweets about ICICI Bank	Linear Regression performed best (R^2 = 0.8741), while KNN showed the worst performance (-0.2820).
Siddartha Reddy et al. [9]	Hybrid KNN-Probabilistic Model, KNN, Naive Bayes, OneR, ZeroR	Stock price trends	Hybrid KNN-Probabilistic model outperformed traditional classifiers, improving stock price prediction accuracy.
Sharma et al. [4]	SVM, ANN, Random Forest	Historical stock prices, investment reports	Automated trading system achieved 86.28% annual profits, enabling passive income generation.

TABLE II

SUMMARY OF MACHINE LEARNING MODELS FOR FINANCIAL SENTIMENT ANALYSIS

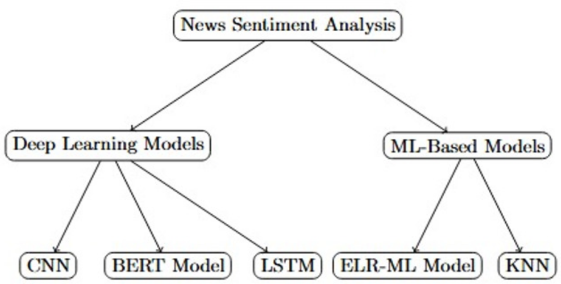


Fig. 5. Visualization of sentiment analysis approaches.

sentiment analysis.

B. CNN Model for Financial Sentiment Analysis

Convolutional Neural Networks (CNNs) are widely used for their ability to capture local dependencies within text data. They are effective in identifying key sentiment patterns in structured financial data, such as tweets and news headlines. CNNs can handle large volumes of data, making them suitable for real-time sentiment analysis in financial markets. For a detailed comparison of CNN models applied to financial sentiment analysis, refer to Table III.

C. BERT Models for Financial Sentiment Analysis

BERT is known as a transformer-based model pre-trained for natural language understanding tasks. Its most distinguishing feature is bidirectional contextual representation to enhance its ability for sentiment analysis and question-answering. This means BERT can capture subtle nuances and relationships between words in a sentence; hence, it is considered useful for financial sentiment analysis, where context is significantly crucial in understanding. Table IV below summarizes the methodologies and performance measures of BERT in financial sentiment analysis applications.

D. LSTM Models for Financial Sentiment Analysis

LSTM networks are specifically built from a variant of RNN to deal with the problem of vanishing gradients. As a result, they are well capable of capturing long-term dependencies in sequential data. The feature is extremely important when analyzing time series data and stock price predictions. In the case of financial sentiment analysis, LSTMs are very efficient in identifying temporal patterns and trends in order to analyze the extent to which previous events impact the current market sentiment. Table V illustrates a general overview of several LSTM models applied in the field of financial sentiment analysis. Finally, Table VI gives even more advanced methods along with their results, thus representing a larger spectrum of techniques applied in this domain.

IV. FUTURE WORK

The domain of sentiment analysis is evolving speedily, especially in the area of financial markets. Grand goals of future studies are now aimed at:

1) The large language models can be improved through the introduction of dynamic weighting techniques. These are required for solving a multitude of complex tasks while improving accuracy in the stock market's sentiment analysis.
2) Companies will use sentiment scores and social media more widely for a variety of reasons ranging from marketing to investments.
3) Research to enhance tools will further increase the accuracy of stock price prediction and sentiment analysis models and make them more common in financial landscape.
4) Future research will look into enhancing data preprocessing and fusion techniques, such as context-based clustering and combine sentiment analysis with his-

Ref.	Datasets	Models	Results
Erkut Mermis et al. [2]	Collected Turkish financial tweets using Python, Tweepy, Twitter API, and MySQL between Jan 2019 and Mar 2020.	Neural Network, CNN, LSTM, GRU, GRU-CNN	CNN model achieved 83.02% for binary dataset and 72.73% for multi-class dataset. GRU-CNN model performed best for binary dataset (80.56%).
Dattatray G. Takale [10]	Variety of stock indices from different market dynamics.	CNN, RNN	Model combining CNN and RNN components showed better performance across multiple stock indices.

TABLE III
SUMMARY OF CNN-BASED MODELS IN FINANCIAL SENTIMENT ANALYSIS

Ref.	Datasets	Models	Results
Michele Costola et al. [11]	Collected 203,886 online articles published between Jan and Jun 2020.	BERT model	COVID-19 news sentiments were significantly related to stock market trends, impacting expectations about the economy.
Jessica Carter et al. [12]	Microblogs and news headlines, reflecting a broad spectrum of market sentiments.	Sentiment Dynamics Analyzer (SDA), RoBERTa	Achieved highest cosine similarity scores, surpassing SemEval-2017 entries by 13.8% for news headlines and 8% for microblogs.
Roumeliotis et al. [3]	Crypto News+ dataset from cryptonews.com, cryptopotato.com, cointelegraph.com.	GPT-4, BERT, FinBERT	Improved investor insights for cryptocurrency sentiment analysis with advanced NLP models, optimizing strategies.
Sstuti D. Mehra et al. [13]	15 stocks from various US sectors using Python's VectorBt library.	BERT-based NLP model	Achieved 84% accuracy in sentiment analysis for financial news, improving stock predictions.
Abi Litty [14]	Data from financial news platforms (Bloomberg, Reuters, CNBC) and online forums like Reddit's r/WallStreetBets.	SVM, Naïve Bayes, RNN, LSTM, BERT	BERT improved classification accuracy, leading to better returns and higher Sharpe ratios compared to traditional methods.

TABLE IV
SURVEY OF BERT-BASED MODELS AND THEIR PERFORMANCE IN FINANCIAL SENTIMENT ANALYSIS

Ref.	Datasets	Models	Results
Bassant A. Abdelfattah et al. [15]	StockNet dataset with tweets and historical stock data for 88 companies from Jan 2014 to Jan 2016.	LSTM model	LSTM model achieved 78.48% accuracy and MCC score of 0.587.
Kwok Ka Tin [16]	Financial news headlines, entities, and their sentiment towards the corresponding entity.	Scikit-Learn, LSTM, XLNet	Logistic Regression from Scikit-Learn performed best with 76% accuracy and 0.76 F1 score.
Aaron Josey et al. [17]	Historical stock data from Yahoo Finance using the yfinance package in Python.	LSTM model	LSTM captured intricate patterns in stock market data, enhancing stock price forecasts.

TABLE V
OVERVIEW OF LSTM MODELS FOR FINANCIAL SENTIMENT ANALYSIS AND STOCK PRICE FORECASTING

Ref.	Datasets	Models	Results
Ali Peivandizadeh et al. [18]	Social media sentiment data combined with stock market data	Off-policy PPO, TLSTM	The proposed approach improved stock market prediction accuracy by integrating social media sentiment with historical stock data, although specific numerical results were not provided.
Pranjali Kasture et al. [19]	BSE Sensex historical data from Jan 2011 to Jan 2021, including daily open, close, high, low, and trading volumes.	Hybrid RNN-LSTM, Random Forest, Support Vector Regressors	R^2 improvement of 0.40% to 5.5% over SVR and RFR models, demonstrating that sentiment analysis improves predictive accuracy.
Devi NSSSN et al. [20]	Stock news and price history data from Aug 2016 to Mar 2023.	FTSEDL model (Ensemble Deep Learning)	Achieved 91.693% accuracy, RMSE of 13.14, and MAPE of 0.02, outperforming recent models.
Hongcheng Ding et al. [21]	Standard and customized financial datasets.	Large Language Models (LLMs)	Improved Mean Squared Error (MSE) by 15.58% and Accuracy (ACC) by 1.24% compared to previous work.

TABLE VI
SUMMARY OF FINANCIAL SENTIMENT ANALYSIS MODELS AND RESULTS

torical data, to increase the accuracy of deep learning models for stock market predictions.

These future directions promise to significantly advance the performance of sentiment analysis in financial markets and beyond, offering better predictive accuracy and risk management for automated trading systems.

V. Conclusion

This review underscores the progress in utilizing sentiment analysis for financial forecasting. The examined studies reveal a variety of models, including Long Short-Term Memory (LSTM), Bidirectional Encoder Representations from Transformers (BERT), and ensemble techniques, each contributing to advancements in predictive accuracy for financial markets. The incorporation of sentiment data from multiple sources, such as social media platforms and financial news outlets, has demonstrated significant improvements in model performance, with accuracy metrics ranging from 76% to over 90%. These findings highlight the critical role of sentiment analysis in enhancing forecasting capabilities and decision-making in financial contexts.

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