

A Review of Machine Learning-Based Sentiment Analysis in Financial Market

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Abstract

Financial market movements are affected by not only previous prices and trade indicators but also by different types of information that is received from different sources such as social media, financial news, corporate/company announcement, analyst reports and economic events and so on. This gives a motivation to researchers for financial sentiment analysis to find signals from unstructured text materials and add this to the financial prediction models. The objective here is to understand financial behaviour after taking sentiments of a trader into account. Machine learning, deep learning and recently transformer based models are greatly improving the capability of financial sentiment detection and also helping to predict market movement effectively. If we look into the research literature from 2020 to 2026, we can see the growing trend of using machine learning and deep learning models for financial sentiment analysis. Most of the research papers in the previous period were based on traditional machine learning algorithms and traditional text classification approaches. But there is a growing trend in the recent research literature of using LSTM networks, transformer based models like FinBERT, ensemble approaches and large language models, which are capable of understanding context and specific peculiarities of financial language. Although these complex models are growing in complexity, it raises concerns like resource requirement, model transparency and interpretability of the predictions. From the literature, we can see that there is a common theme that suggests that information in textual sentiment may be able to capture some information that is not easily captured by numerical market variables. Sometimes, the variation of results could be attributed to difference in characteristics of the market, data sources, time period of the studies, prediction horizons, modelling approach and so on at that point in time. This is a strong indication that the characteristics of the data are playing a very strong role in the effectiveness of the sentiment analysis. From the existing literature it seems that it is more effective to use sentiment information along with traditional financial variables. As a standalone predictor it is not so effective. But there are some important issues that have not been explored enough for this field despite advancements. These are integration of multi source information, appropriate temporal alignment of heterogeneous data, avoiding information leakage, model robustness evaluation for varying market conditions, handling computational requirements and at the same time model interpretability. These problems open up a detailed discussion on combined financial prediction models. If we develop an integrated framework which can use financial text sentiment and market variables together, we may get a more robust approach to predict financial markets. This framework should take into account information timing and also model interpretability. Indian financial market can be a good setup to carry out this type of investigation. We can get multiple views of changes in market sentiment using company disclosures, news, investor talks, market data etc. which can be studied along with market behaviour. After which it can be collected and processed for a prediction model. We need to consider how different sources of information are combined in a thoughtful way. For example, market data is captured at regular time

intervals whereas news articles, corporate announcements, social media posts are available at non-regular time points. Information timing of release of textual information is important for understanding the linkage with future market movements. If we mistakenly consider information which is not available at prediction time in the model then it may give wrong figures for model performance. The issue is not just technical. It is more important to have model transparency when these models are used for decision making. Also when it is being used as a base for research.

Keywords: Machine Learning, Sentiment Analysis, Financial Market, Stock Market Prediction, NLP, FinBERT, Deep Learning, Investor Sentiment, Financial News.

Introduction

Predicting future movements in financial markets is an extremely challenging research area. Market prices are influenced by multiple factors, including firm performance, macro-level changes, investor sentiments, and unexpected events. Therefore, many researchers have focused their efforts to analyze past market prices, trading volumes, technical and fundamental data. The aim was to identify possible patterns that could help with prediction. These variables contain valuable information regarding the market behavior, but they may not contain all the possible information that investors can use when making investment decisions.

An important part of the available information for investors is textual information. Information such as financial news, corporate information, social media conversations, analyst opinions, etc. often contain information regarding investor sentiments, uncertainty, firm outlooks, and reactions to market changes. This information could potentially influence investors' decisions even before it becomes evident in conventional numerical indicators. As a result, financial sentiment analysis has become a vital research area which allows the conversion of textual information into sentiment metrics that can be incorporated into quantitative financial models.

Techniques used to perform financial sentiment analysis have evolved over time. Early studies largely relied on sentiment dictionaries and traditional machine-learning techniques such as Support Vector Machines, Random Forest, Logistic Regression and Naïve Bayes. With increased availability of financial text and improvement in computational techniques, researchers started exploring neural network models such as Convolutional Neural Networks (CNN), Long Short-Term Memory (LSTM). More recent studies are increasingly focusing on transformer models such as BERT and its finance specific version FinBERT. These models are believed to better capture contextual information present in financial texts. With the advent of Large Language Models, the scope of sentiment analysis has expanded further, particularly for understanding complex financial narratives and for integrating information from multiple sources. Despite these advancements, there is no clear consensus in literature regarding the efficacy of sentiment information in predicting financial markets. Results may vary due to factors like the source of data, market conditions, prediction period, sentiment extraction techniques, model type and evaluation criteria. Therefore, overall model accuracy may not be sufficient to understand the utility of sentiment information. This review aims to examine the literature more broadly to understand how different sentiment analysis techniques, information sources, modelling techniques and evaluation criteria affect financial prediction results. The focus is particularly on the evolution from traditional machine-learning techniques, to deep learning, to transformer based models and to the recently emerging large language model techniques. In addition, this review identifies methodological challenges and inconsistencies pointed out in previous studies. Based on the review, this study highlights potential research areas that need further exploration and discusses how such research gaps can be addressed in Indian financial markets.

Review of Literature

• Traditional Machine-Learning Approaches

Traditional machine-learning models are still used in the financial sentiment research area mainly due to their relatively simpler interpretability, computational efficiency and suitability for structured features. Several studies have used Support Vector Machines, Random Forest, Logistic Regression, Naïve Bayes and Multi-layer perceptron's to analyse different combinations of financial text, social media

data and market data. For example, Gumus & Sakar (2021) used sentiment information, stock prices and technical data. They observed better results when compared with models using only numerical data. Similarly, Khedr et al. (2021) analyzed Twitter and StockTwits data using several traditional classifiers. These studies suggest that sentiment can be useful to supplement numerical market information. However, they also highlight the importance of features engineering, data quality and dealing with characteristics of financial text.

- **Deep Learning and LSTM-Based Models**

The incorporation of deep learning techniques to a larger extent has mainly been an attempt to overcome the shortcoming of the manually designed features. Deep neural architectures are capable of automatically learning the nonlinearities present in the data and also are able to capture the relationship between the sentiment in text and the market movement. For example, a combination of the investor sentiment classification through CNN followed by the stock price prediction through LSTM has been reported by Jing, Wu and Wang (2021) showing better results with the integration of sentiment. Hybrid PCA-EMD-LSTM framework has been proposed by Srijanon et al. (2022). In a different study, LSTM and Random Forest have been used to integrate the Indian stock data with sentiment and macro-level factors (Darapaneni et al., 2022). The above studies together indicate that sentiment is likely to yield better results when it is considered as a part of the integrated market data rather than a predictor itself.

- **FinBERT and Transformer Models**

The preference for using transformers is an important methodological shift in the domain of financial sentiment analysis. Financial texts are often known to contain expressions that require a contextual understanding. It is not always possible to rely on general sentiment tools for a consistent outcome in such cases. Given the nature of financial texts, FinBERT was developed as a finance-specific model and has become a popular choice for the purpose of sentiment extraction specific to finance. Jiang and Zeng (2023) have integrated sentiment from financial news based on FinBERT and LSTM-based prediction. In another instance, a combination of FinBERT with LSTM was used to predict S&P 500 (Kim, Kim & Choi, 2023). Similarly, there have been studies pertaining to NSE data that have shown the possibility of using finance-specific transformer models for the Indian market. However, transformer models require much larger computational resources and the additional complexity in itself need not always lead to better prediction performance.

- **Hybrid Models, Large Language Models and Multi-Source Sentiment**

Newer studies show a growing inclination to explore the relationship between the modelling techniques and the nature of data. Shobayo et al. (2024) have compared FinBERT, GPT-4 and Logistic Regression and, surprisingly, have found logistic regression performing well in their experimental setting. It is an interesting finding which highlights the importance of not always equating complex model with better prediction. Kirtac and Germano (2024) have used a large database of financial news articles and have found predictive association between LLM sentiment and future returns. Recent studies have also explored a combination of social media and news data and the dynamic impact of sentiment. Thus, the overall trend seems to be evolving from polarity-based sentiment classification to more contextual, multi-source and economically relevant predictions.

- **Systematic Literature Review Matrix**

Table 1 represents various different columns used such as the dataset, data source used, Sentiment technique, Machine-learning model applied, variables and evaluation measures involved, and the key result covering the limitation and research gap identified.

Table 1: Systematic Literature Review Matrix of Selected Studies on Financial Sentiment Analysis and Market Prediction

Author / Year	Dataset / Market	Data Source	Sentiment Technique	ML / Prediction Model	Variables	Evaluation	Key Result	Limitation	Research Gap
Jing et al. (2021)	Chinese stock forum / China	Stock forum	CNN sentiment	CNN + LSTM	Text + price	Accuracy, RMSE	Adding sentiment improved the baseline prediction	Market-specific evidence	Cross-market validation
Gumus & Sakar (2021)	News + prices / Turkey	Financial news	Sentiment analysis	Traditional ML	News + technical data	Accuracy	Combining textual and market information improved prediction	Limited deep-NLP comparison	Transformer comparison

Khedr et al. (2021)	Twitter / StockTwits / USA	Social media	Sentiment classification	SVM, RF, LR, NB, MLP	Tweets + stock data	Accuracy, F1	Social sentiment provided useful predictive information	Social-media noise	Multi-source framework
Srijiranon et al. (2022)	Market + sentiment / Thailand	News and social data	Sentiment analysis	PCA-EMD-LSTM	Price + sentiment	RMSE, MAE	Hybrid modelling improved forecasting	Complex preprocessing	Generalisable framework
Darapaneni et al. (2022)	Indian stocks / India	News, social and market data	Sentiment analysis	LSTM + RF	Price + sentiment + macro	RMSE	Sentiment added predictive information	Limited stocks and period	Broader NSE data
Pattewar & Jain (2022)	Twitter / India and global	Twitter	Optimised sentiment	BiRNN	Tweets + stock data	Accuracy, F1	Optimised features improved prediction	Twitter-specific data	Add news and corporate data
Xiao & Ihnaini (2023)	Twitter + stock data / USA	Twitter	BERT / FinBERT	ML classifiers	Sentiment + trend	Accuracy, F1	FinBERT was useful for trend prediction	Limited information sources	Multi-source testing
Jiang & Zeng (2023)	Financial news / financial market	Financial news	FinBERT	FinBERT + LSTM	Sentiment + movement	Accuracy	Sentiment showed predictive value	Limited scope	Cross-market validation
Kim et al. (2023)	Financial text / USA	Financial news	FinBERT	FinBERT + LSTM	Sentiment + S&P 500	RMSE, MAE	FinBERT-LSTM combination was effective	Computational cost	Compare with simpler models
Roy & Debnath (2024)	Previous studies / multiple markets	Published literature	Literature review	ML + sentiment	Review evidence	Review findings	Highlighted data and generalisation issues	Secondary evidence	Empirical validation
Shobayo et al. (2024)	Financial news / Nigeria	Financial news	FinBERT / GPT-4	FinBERT + GPT-4 + LR	Sentiment + index	Accuracy, F1, ROC-AUC	LR performed strongly in their setting	Single-market design	Broader temporal validation
Kirtac & Germano (2024)	965K articles / USA	Financial news	BERT / FinBERT / LLM	LLM-based trading	Sentiment + returns	Portfolio / returns	LLM sentiment showed predictive value	Computational cost	Explainable and cost-efficient models
Mehrkian & Davari-Ardakani (2025)	Sentiment + index / Iran	News + market	Sentiment integration	Integrated ML	Sentiment + quantitative data	Forecasting metrics	Combined modelling improved forecasting	Market-specific	Cross-market testing
Ballesteros & Miranda (2025)	Fundamental + technical + sentiment / multiple markets	Market data	Sentiment analysis	Neural network	Fundamental + technical + sentiment	Forecasting metrics	Multi-factor integration was useful	Market scope	Broader validation
Chauhan et al. (2025)	Financial website data / financial market	Financial websites	Sentiment analysis	Deep learning	Text + market data	Prediction metrics	Sentiment enhanced prediction	Limited data scope	More information sources
Chaudhari & Mahajan (2025)	Market + technical data / financial market	Market data	Sentiment analysis	Ensemble / DRL	Price + technical variables	Trading metrics	Advanced ML showed potential	Text integration limited	Richer textual sentiment
Zhao & Tang (2026)	Previous studies / multiple markets	Published literature	Systematic review	AI / transformers	Review evidence	Review findings	Transformer use is increasing	Secondary evidence	More empirical Indian studies
Khalil (2026)	Reddit, Twitter, Bloomberg, Reuters / multiple sectors	Social media and news	Transformer sentiment	Hybrid LSTM-RF	Sentiment + market data	Forecasting metrics	Multi-source modelling improved robustness	Model complexity	Explainability and deployment

Key Findings from the Literature

The review of existing literature shows that financial sentiment has promised an extra source of information for predicting markets even though many methodological gaps are still open.

With the in-depth study of machine learning, deep learning and transformers based models. While comparisons are made between different models. The datasets and time frame, features, evaluation metrics considered are different making it difficult to identify whether the improvement is because of model i.e. modelling approach or the way data is being handled, feature representation, experiment etc. Overall there is need to look at a study having consistent data and evaluation metric.

Second, most of the studies consider sentiment and numeric market variables either in isolation or with very simplistic combination. Some studies reveal the additional value of sentiment with price volume technicals and fundamentals. But there are few studies to look in depth about what information and how much information can be integrated in one time aware framework. Important is how well the timing of news release, corporate disclosure, analyst opinions, market observations etc are timed accurately. Otherwise there may be a chance to leak unobservable information at the time of prediction in the model leading to information leakage. This will lead to overfitting results.

Thirdly, literature mostly caters to one or a few data sources, i.e., news and social media sites. Corporate specific disclosures, analyst recommendations and economic announcements are seldom incorporated as part of one integrated prediction framework. This becomes important because different sources may contain different pieces of information, which might capture a part of investor expectation. It might be useful in different timeframes. Together considering all these sources can give a clearer picture of the information which is available in the market.

Fourthly, how much value is there with complex models? Transformers based and large language models are capable of contextual representation which is lacking in many of the traditional models. But on the other side complexity of the model, high computation cost and less interpretability is raising practical issues. Moreover, just because it is showing better statistical metrics, doesn't always translate into economic results. So along with statistical metrics i.e. accuracy (F1 score), MAE, RMSE etc we need to look for financial metrics such as return, risk adjusted return, drawdown and transaction cost.

Finally, there are some studies which try to cover all the aspects in the Indian financial market. Indian financial market provides an environment where we can compare head to head the impact of combining company disclosures, financial news, investor sentiment with traditional market variables. But multi source, time aware, integrated and explainable framework with comparison on same criteria. Which considers statistical prediction performance as well as economic usefulness. This framework is still relatively underexplored.

Therefore, the main research gap is not about another sentiment analysis model. It is about a framework which can demonstrate the situation, when and how much additional predictive information financial sentiment can provide with traditional market variables in consistent environment. To address this gap one needs to consider temporal alignment of different information sources, comparison between modelling approaches with consistent evaluation metric, control information leakage, how well model generalise with time, considering both prediction as well as economic usefulness. Which can give us evidence of what is the additional value of financial sentiment especially for market prediction.

Research Gaps

Reviewing the existing literature in this way brings out several areas that call for further investigation, and these form the basis for the study proposed here.

- **Limited Integration of Multiple Information Sources**

To summarize, as per current literature, financial sentiment is useful to market prediction. However, a multi source time aware framework which can consistently evaluate additional predictive information of sentiments with traditional market variables, taking care of information leakage, generalisation, explainability and economic relevance in particular for Indian financial market is needed.

- **Unclear Incremental Contribution of Sentiment**

In previous work, although it has been noticed that there are some improvement after adding sentiments, sometimes it may not be conclusive if the improvement is due to the addition of sentiments or some other aspects in data and modelling. In this sense, this study especially emphasizes to compare two different groups of model: One group is based on only traditional numerical market variables. The other group is integrating numerical variables with financial sentiments. For example, numerical variables can be OHLC prices, trading volume, technical indicators, relevant macro-economic data. In this way we can focus more to study about contribution of sentiment.

- **Need for Greater Evidence from the Indian Market**

Majority of previous work focused on market like USA and other developed financial systems. Although they give some methodology insight which is very valuable but the structure of market, investors, information and disclosure may be different in each country. Therefore, this study focuses on Indian market with NSE listed company's information. In this way we may observe the same relation as found in international research, and also try to find some special facts related to India.

- **Importance of Maintaining the Correct Information Timeline**

Financial prediction very much relies on timing for information. Ideally, a model predicting the market should only use the information which can be known at the time when the prediction is made. For example, if there is a corporate news at after market hours then it should not be used to predict closing price of that day. In this study, we shall also consider temporal consistency between textual information and market data. This is important not only for limiting the information leak but also to make the evaluation more close to real world performance if model is used in real-world.

- **Need to Connect Statistical Prediction with Economic Usefulness**

Most of previous work show statistics like accuracy, f1-score, MAE, RMSE. These statistics are valuable to compare the predictive performance but by itself not sufficient to check if final predictions

have any financial significance. In this sense, this study tries to look at both the statistical as well as economically significant metrics. Apart from regular prediction measures we can consider some measures like return, sharp-ratio, maximum drawdown, transaction cost (if some appropriate trading strategy is there). Also, we can use explain-ability techniques to check the contribution of sentiment and market variables in the predictions.

Relevance of These Gaps to the Proposed Study

Based on these gaps, research will be designed. This research is not intended to develop another sentiment classification model. This is intended to find if there is any helpful information present in financial sentiment that is useful compare to regular market variables. In which situation it is useful. For that a research design which integrates textual and numerical data is required. And information should be utilized as per timing when information is available.

Research framework shall include following four aspects: Multiple source of financial data. Timing of the data. Model comparison. Thorough evaluation. We can get models from traditional machine learning. Under this, we can test model like LSTM. Transformer based model (FinBERT and better model like these). Under these conditions. The models shall be compared on the basis of accuracy.re. not only this but also other aspect of performance. Performance in different situation. Processing power required. Explain-ability. Real-world performance (in financial term if possible).

The study also provides an opportunity to observe how the sentiment results from different parts of the world can be applied to the Indian financial market by analyzing the data related to NSE and particular companies. The anticipated outcome will be on two fronts, ways of doing things and new findings. The ways of doing things will include combining different types of data in such a way that time factor is considered. The new findings will include measuring how sentiment adds up to market prediction when the data for India is used in under the testing conditions. This study is particularly trying to fill the gap by providing a way to study what multi-source financial sentiment really adds to the market prediction in a time-aware and well compared way. Especially, when it comes to stock market.

Proposed Research Direction

The results of this review will be able to facilitate in designing the financial market prediction approach. The study will combine multiple sources of sentiment (financial news, NSE corporate announcements, social media discussions, analyst recommendations, relevant economic updates) instead of relying on a single source of sentiment. These sources differ in their structure and release times, hence the data will be matched based on when the information is released for the market. After matching the data, sentiment will be extracted from the text data by using the known financial word lists and advanced language models such as BERT and FinBERT.

The sentiment signals will be combined with market data (Open, High, Low, Close, Volume - OHLCV), returns, and few popular technical indicators. Important part of the study will include comparison of model results that are designed using numerical market data with models that also include sentiment features. A wide variety of approaches will be tested including Logistic Regression, Support Vector Machine (SVM), Random Forest, XGBoost, LSTM, BiLSTM, and transformer models. By using all these models for the given dataset in the same time range, this study will enable a fair comparison to test if there is really an improvement in prediction with more complex models.

The model performance will not be evaluated in terms of statistical metrics. For example, accuracy and F1-score are good metrics for classification problems, MAE and RMSE are good for variables such as stock price. Only statistical accuracy does not provide much insight into how useful the model will be in real trading application. Hence, if it is possible to define a trading strategy, then we will look at returns, Sharpe ratio, maximum drawdown, transaction costs. Tools for explainability, such as SHAP, will provide insights on how much each market variable or sentiment features affect the model decisions. It will provide insights not only about performance but what drives the predictions.

Broadly speaking this study is aligned with a recent trend in the field of financial sentiment analysis to transition from source basic financial sentiment indicators to advanced (integrated of multiple information sources) financial sentiment models. In particular at the time of the study, the research will not take it for granted that advanced sentiment models would be more effective. The study will instead thoroughly examine the role of sentiment, the impact of integrating multiple sources, and the effectiveness of advanced models vis-a-vis simpler (and interpretable) ones. The emphasis on the study

being over time aligned data, evaluating the model consistently, as well as relying on both statistical and economic metrics would help in gaining insight into the real impact of financial sentiment over stock market behavior particularly in India.

Conclusion

Financial sentiment analysis has grown in recent years. Initially, sentiment analyses often use polarity scores or simple machine learning. Now deep learning, transformer models, or large language models are often adopted. From the reviewed papers, it shows the importance of words in documents to predict the market movement. It is important to note that sentiment is not always the same. The usefulness of sentiment varies based on the type of text, market, the horizon, sentiment measure, and model.

Some important finding of these studies: - financial sentiment should never be used as a standalone predictor; it cannot substitute market data, sentiment has to be used together with price, volume, return, technical indicators, etc. other facts about market; - further research should be done to build more individual sentiment classifiers; - more efforts need to be spent on analyzing if there is a new predictive power added by sentiment that is not already included by other variables.

This is a scope for research in Stock Market. By integrating the News (NSE), Company Announcements, Analyst Reports, Social Media etc. (text data) and data available for the market you can provide a complete information to an investor. It is important to consider the time factor for data, comparison among models, model stability and the gap between statistical correctness and real economic worth.

Carefully timed and aware analysis of all of the factors may be able to demonstrate that when and how multi-source financial sentiment is better at stock market prediction.

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