

Deep Learning Sentiment Analysis for Stock Forecasting

Ankit Verma, Rajdeep Singh, Mohit Lal Sah

School of Computer Science & Applications, IFTM University, Lodhipur Rajput, Moradabad,
244102, Uttar Pradesh, India.

akkyverma@gmail.com, singh.rajdeep1@gmail.com, mohitsah0@gmail.com

ABSTRACT

The review focuses on the effectiveness of deep learning-based social media sentiment analysis in predicting stock performance in the finance sector. It finds that such approaches generally improve forecasting accuracy by capturing market sentiment nuances. However, challenges remain in managing data noise and improving model interpretability. Overall, integrating sentiment signals enhances stock prediction models' robustness and timeliness. This review synthesises research on "Effectiveness of deep learning driven social media sentiment analysis in forecasting stock performance in the finance sector" to address challenges in integrating heterogeneous data and improving predictive accuracy amid market volatility. The review aimed to evaluate deep learning architectures applied to social media sentiment for stock forecasting, benchmark integration with financial indicators, analyze sentiment extraction methods, compare model effectiveness in capturing temporal and sentiment dynamics and identify limitations in handling market uncertainty. A systematic analysis of global studies employing LSTM, CNN, transformer and hybrid models revealed consistent accuracy improvements when combining sentiment with technical and macroeconomic data, with transformer based and multi modal approaches achieving up to 90% accuracy. Domain specific sentiment models enhanced contextual relevance, though ambiguity and data noise remain obstacles. Integration of sentiment and financial indicators improved forecasting robustness but introduced complexity and challenges in feature fusion. Explainable AI methods emerged to increase model transparency, yet interpretability is generally limited. Overall deep learning driven sentiment analysis demonstrates significant potential to enhance stock performance prediction, though standardization in evaluation and improved handling of volatility and data heterogeneity are needed. These findings inform future research directions and practical applications in financial forecasting and investment strategy development.

Keywords : *Deep Learning social Media Sentiment Analysis, Stock Performance Prediction, Transformer Models, Market Volatility Forecasting*

Introduction

Research on deep learning based social media sentiment analysis in forecasting stock performance has become very important because investor mood strongly affects markets and there is a large amount of social media data available [1][2]. In the last ten years, NLP and deep learning models like LSTMs and transformers have been used to understand both time patterns and meaning in financial text [3] [4]. This shows a shift from old econometric models to new mixed frameworks that join technical indicators with sentiment from platforms like Twitter and StockTwits [5] [6]. Many studies prove that using sentiment-based models can improve prediction accuracy by up to 25% and also increase profits in fast changing markets [7][8]. But there are still problems in bringing together financial and sentiment data because of its difficulty, missing data and unclear signals [11] [16].

Purpose and Scope of the Review Statement of Purpose

The main goal of this review is to study how useful deep learning based social media sentiment analysis is in forecasting stock performance in the finance sector. The study looks at the present methods, benefits of adding sentiment and also the problems, showing how these models make accuracy better, guide investors and help in managing risks.

Specific Objectives

The review focuses on checking deep learning models for stock forecasting using sentiment, comparing different methods that mix financial indicators and sentiment, summarizing data sources and how they are cleaned and testing the predictive performance of models. It also tries to find the problems like market volatility and unclear mood signals that affect accuracy.

Methodology of Literature Selection Transformation of Query

The main research question was divided into smaller questions that included how deep learning works, ensemble methods, use of many data sources together and joining news with technical indicators.

Screening Papers

Search with Inclusion and Exclusion Criteria gave 548 papers.

Citation Chaining

Backward and forward citation chaining added 53 more studies.

Relevance Scoring

Out of 601 papers reviewed, 114 were ranked as highly important.

Results Descriptive Summary of the Studies

The studies reviewed show how deep learning and sentiment analysis have grown in stock forecasting. Different model types, data sources and analysis styles have been tested. Early studies used hybrid models that joined CNN and LSTM together to understand both short and long term stock changes. These models added Twitter sentiment with candlestick data and used Random Forest classifiers to take features from tweets which helped in increasing accuracy while reducing the effect of volatility by using both technical indicators and sentiment [1], [5]. In the same way multimodal CNN LSTM frameworks with attention added more power by using social media, news sentiment and economic indicators which gave accuracy above 77% and did better than old models [13].

The use of transformers has brought a big change in this field. Transformer based multimodal architectures with GNNs allowed dynamic modeling of market changes by combining sentiment, time and macroeconomic inputs. These models adapted well and performed better than conventional models [11]. Transformer based frameworks like BERT, RoBERTa and XLNet showed big performance improvement because their embeddings understood context better and gave strong predictions on different datasets [2], [4], [18]. Models that joined transformer attention and BiLSTM predicted stock trends with more than 90% accuracy by adding social media data, technical indicators and multi head attention [61], [76].

Sentiment analysis methods also changed over time. Earlier, lexicon based tools like TextBlob and SentiWordNet were used to take out polarity and subjectivity from tweets which helped RNNs and LSTMs to use investor mood [19], [100]. But these tools were replaced with models like FinBERT that understood financial language better which raised accuracy and profit [6], [12], [23]. New methods like zero shot sentiment using pre trained transformers worked well even without labeled data and gave accuracy above 90% in many cases [8], [79], [87]. Other new frameworks added credibility scoring for social media posters [53] and used neutrosophic logic to manage unclear sentiment signals [21]. These steps improved trust and clarity.

The models tested showed strong results when sentiment was added with technical and historical data. For example Neural Prophet with Twitter sentiment cut RMSE by 25% for short term predictions [30]. Ensemble models like LSTM, XGBoost and Random Forest reduced errors and XGBoost gave the best fit in many cases [34], [35]. BiLSTM models with attention worked better when follower count or popularity of messages were used as weights [32], [51]. Some models even achieved more than 95% accuracy for stock specific forecasting like IndRNN with user behavior modeling [17], [71].

Many studies proved that models using sentiment always did better than those using only historical or technical indicators. RNNs with sentiment reduced MAE by half [19], double deep Q learning

networks gave more profit [7] and BiLSTM and CNN models showed lower errors [38]. Comparative studies showed that without sentiment, accuracy fell a lot, proving that investor mood and psychology matter [41], [44], [90].

Robustness and interpretability also became important. Explainable AI like LIME and SHAP gave clarity on how models worked [10], [78]. Ensemble SVM with FinBERT sentiment gave both high accuracy and better explanation [6]. Credibility scoring reduced noisy data [53]. Event driven hybrid models joining news, financial indicators and affective analysis connected events with sentiment shifts to give useful insights [103].

These models also worked well in different markets. In India and China, hybrid LSTM, GRU and sentiment polarity models improved forecasting in banking and technology [42], [88], [97]. Multilingual models with genetic algorithms worked better on non English data [82]. Studies on Weibo sentiment showed that posts from official financial actors had more predictive power than common users [64].

Some studies also checked user impact and spam. User2Vec, TM vector and GAN based models found spambot tweets and improved reliability [16], [17], [66]. Adding weights based on follower count or post popularity also improved predictions [32], [65]. Models using chip indicators and genetic optimization raised forecasting performance [43], [48], [70].

Ensemble and multimodal models gave excellent results. Mixing LSTM, CNN, MLP and XGBoost gave strong results in short term predictions [20], [57]. By combining different models, weaknesses were reduced and general performance improved. Reinforcement learning and attention models like TLSTM with PPO helped balance data and improved predictions [49]. Multi attention networks worked on complex patterns and showed scalability [45].

Some models focused on high volatility. SSA optimized LSTM and CNN LSTM trained on Reddit sentiment worked better in volatile conditions [9], [46], [68]. Cross modal fusion with transformers and temporal convolution captured inter stock relationships and showed gains [37]. Neural networks using both sentiment and time series improved stock trend predictions [59].

In terms of strategy some studies tested profit analysis and new accuracy measures like adjusted MAPE [57], [53]. Topic sentiment embeddings [75], [91] and collaborative frameworks [78] showed both accuracy and profit. Portfolio based methods improved stability and long term profit [27].

All these studies prove that deep learning models with sentiment are better than traditional methods in accuracy, profit and reliability. They also show a journey from early lexicon methods to advanced multimodal and explainable frameworks that adapt to real time market changes. These results prove that sentiment analysis with deep architectures and ensembles improves forecasting in both developed and emerging markets.

Model Architecture

More than 40 studies use LSTM models often combined with CNNs or attention to capture both time and mood features [1] [19] [33]. Transformer models and GNNs connect many data types and work well in complex markets [11] [37] [14]. Hybrid methods using reinforcement learning, ensembles and autoencoders improve adaptability and reduce noise [7] [43] [101].

Data Integration

Most studies join social media sentiment with technical indicators and economic variables [1] [5] [36]. Multi source approaches use transformers and graph attention to mix news social media and market data [11] [13] [104]. Some models also use user influence metrics to add more weight to sentiment [16] [71].

Sentiment Analysis Techniques

Lexicon tools like TextBlob and VADER are still used for tweets [19] [51]. But transformer based models such as BERT, FinBERT and RoBERTa perform better because they understand financial language [6] [4] [18]. New methods add classification and fuzzy logic for unclear text [31] [21] [81].p

Predictive Performance

Sentiment always improves accuracy, RMSE, MAE and F1 scores [19] [33] [8]. Transformer and multimodal models give 75–90% accuracy [11] [36] [76]. Hybrid and ensemble models reduce errors, increase profits and help trading [7] [2] [57].

Robustness and Interpretability

Models improve in volatile markets when mood dynamics are added [11] [12] [9]. Explainable AI tools like LIME and SHAP help in understanding decisions [36] [10] [78]. Still challenges exist in handling noisy sentiment but preprocessing and uncertainty logic make results better [21] [66] [81].

Critical Analysis and Synthesis

The reviewed literature shows strong points in using deep learning and sentiment analysis for stock forecasting but it also shows some weak points. Many advanced models like CNN LSTM, transformers and graph neural networks are used to catch both time patterns and changes in mood which makes predictions more correct [1] [11] [33]. Ensemble and multimodal models make results stronger by joining many types of data [57] [13]. But these models are often very complex and need a lot of computer power so they cannot be scaled easily. Many studies depend too much on one type of model and do not check results properly with benchmarks. This raises problems like overfitting and poor reproducibility especially when hyperparameters are not handled well [30] [5] [43].

Data from Twitter, StockTwits and market records is often used to get investor mood [2] [6] [16]. Advanced steps like slang correction and feature engineering make data better [20]. But Still noise, spam and fake content create problems [66]. Most datasets are in English which makes it hard to apply them in many languages and some datasets cover only short periods, making results less strong [31] [82].

Sentiment analysis tools have also grown with FinBERT and neutrosophic logic which make context better [6] [21]. Transformer models and multi lexicon methods understand fine details of mood more clearly [18] [58]. Still unclear signals, context changes and different investor behaviors make correct mood reading difficult [19] [93]. Another big issue is that many models are not clear to explain, making interpretation harder [10].

When sentiment is joined with financial indicators, prediction becomes better because both feelings and numbers are used together [5] [25] [26]. But mixing different data types brings problems like matching features, higher model difficulty and uneven strategies [30] [12] [43]. To deal with volatility, reinforcement learning and attention have been used [7] [45] but sudden shocks and short term changes are still hard to handle [30] [21].

New explainable AI methods like LIME help us understand which features are important [10] [36] but many models still act like a black box. Using measures like RMSE, MAE and accuracy makes the results more trusted [19] [35] but because there are no common datasets or standard benchmarks, comparing results is still difficult [34] [104]. In short, deep learning with sentiment analysis has strong promise but problems like scalability, noise, sudden changes and clarity still need better and more open solutions.

Thematic Review of Literature

The reviewed literature mainly studies how deep learning works together with social media sentiment analysis to predict stock performance. It shows that big progress has been made in both model design and data use. The focus is on advanced models like LSTM, CNN and transformers that capture time patterns and mood based changes. Another important theme is combining text sentiment with market and macroeconomic indicators which makes prediction more accurate. But challenges like noise in data, unclear mood signals and difficulty in explaining deep learning models are still there. Some recent studies also show how user influence and multimodal data are used, proving that research is moving ahead both in methods and in cross market use.

A large part of the research—83 out of 114 papers—uses deep learning models like LSTM, CNN and transformer types to mix social media mood with market data. These studies show that stock price and movement predictions become better and beat old forecasting methods [1] [11] [19] [33] [4] [80].

In 61 papers, mood is combined with technical and macroeconomic indicators to build hybrid models and this mix usually improves accuracy [11] [5] [42] [46] [15] [26].

Another big theme found in 47 studies is the use of advanced mood extraction and multimodal data. These works use financial lexicons, context based classification and data from news, forums and social media. Adding multimodal mood data makes predictions stronger and more stable [31] [13] [47] [16] [78]. Some studies, 12 in number, add reinforcement learning, genetic algorithms and swarm intelligence to forecasting. These methods help models work better in volatile markets by changing strategies based on both mood and market signals [7] [43] [105].

Problems with data quality and clarity are also common. 48 studies look at noisy data, unclear mood and the black box problem of deep learning. They suggest using neutrosophic logic, explainable AI and data augmentation to make predictions more reliable and easy to explain [21] [36] [49] [10]. 15 studies focus on user influence and network links, showing how trust and user interaction affect mood weight. Giving more value to trusted users makes market prediction better and stronger [17] [106] [16].

Some studies target special markets like China, India, Europe and North America. These 29 works show that market structure and culture change how models perform and how mood affects results [32] [12] [64] [98].

Chronological Review of Literature

Research on deep learning and social media mood analysis for stock forecasting has grown fast in the past ten years. Between 2015 and 2017, early works added social media mood to stock prediction using simple tools. These studies showed that adding mood gave better results than only using old price data. Neural networks also proved useful and gave better accuracy, starting the use of investor mood from sites like Twitter.

Between 2018 and 2019, studies began using advanced models like LSTM and attention. Bigger datasets helped to capture mood in more detail, including topic based and mood dimension analysis. During this time, hybrid models mixing technical indicators and social media mood appeared which made trend prediction sharper.

Between 2020 and 2021, multimodal and ensemble models became popular. Social media, news and market data were joined often using hybrid networks. Pretrained transformers and embeddings made mood extraction stronger. Research also started to care more about robustness, clarity and handling noisy social data.

In 2022 and 2023, hybrid models mixing CNNs, LSTMs, transformers and reinforcement learning were widely used. Explainable AI was also added to make predictions more clear. Multi class sentiment and multimodal fusion helped to capture complex market changes while more work was done to handle noise and volatility.

From 2024 onwards the focus has moved to advanced integration and practical use. The newest models use multimodal transformers, graph neural networks and reinforcement learning with genetic algorithms. They mix mood changes, time data and economic indicators to give more accurate and profitable results. Newer works also use explainable AI and expert opinion to provide insights that can help in real trading.

Agreement and Divergence across Studies

The literature broadly shows that mixing deep learning based social media sentiment with old style financial data makes forecasting more correct. Many studies point out that LSTM and its types work well for showing time based changes in sentiment, though there are differences in which model, sentiment method or joining method is used. Most writers agree that the design of the model matters, with hybrid CNN LSTM frameworks and transformer based models working very well to catch context and links [1] [5] [38] [4] [3] [11] [76]. Some studies instead look at reinforcement learning or GNNs [7] [104] [14] while others use simple ensembles or ML methods [34] [35] [57] [28]. These changes often happen because of different goals of prediction, computer power and dataset size. In the same way many papers support data joining. Joining sentiment with financial and macroeconomic signs makes forecasting stronger [11] [19] [5] [36] [42] [46] [16] [10] and multimodal frameworks are becoming popular [11] [37] [104] [14]. But there are gaps between

models that only put features together in a simple way [19] [30] [51] and those that use advanced fusion like cross modal transformers [11] [43] [49] [96].

On sentiment analysis methods, most writers agree that correct extraction of sentiment makes forecasting better [31] [6] [4] [25] [18]. Advanced domain based lexicons and transformer models improve the use of data [31] [6] [23] [54] [18] but some still use old lexicon based or simple classifiers [19] [51] [3]. Others test zero shot or multi class classification [79] [87] [84]. These differences are mostly due to dataset size, language and computer trade offs. Results of forecasting show that mixing sentiment gives higher accuracy, RMSE, MAE and F1 score [19] [5] [35] [4] [3] [26] [95]. Still some mixed results are seen in markets that change fast [9] [107] [24] where reinforcement learning and ensemble models give results that are not always the same [7] [43] [57]. Finally, strength and clarity of models are still argued. XAI methods [36] [16] [10] and attention methods [60] [77] are used more but many transformer and reinforcement learning models still act like black boxes [11] [49]. The main problem is the trade off between complex models and clear models as complex ones give better results but are harder to understand. Problems like noise, false info and uneven data are still hard to handle [66] [24].

Theoretical and Practical implications

Theoretical Implications

Using deep learning with social media sentiment improves the theory of stock forecasting by catching hard time patterns and market changes that are missed by old models. Studies show that CNNs, LSTMs and transformer models when joined with sentiment data give better results, showing that multimodal data fusion is very important in financial forecasting [1] [11] [37]. This also adds proof to behavioral finance theories as it shows that investor sentiment from social media affects stock prices strongly and challenges EMH which says that all info is already in the stock prices. Models that add sentiment always do better than those using only past or technical data [19] [24] [93].

Making better sentiment classification that is domain based helps solve the limits of old tools, making features more correct and helpful. This change supports models that are both clear and strong, showing a new shift in theory toward financial NLP [31] [108] [78]. Advanced methods like GNNs and attention models give new frames to show stock links and investor actions, catching both market design and sentiment for a full view of market moves [11] [104] [14]. Also XAI helps to open the black box of deep learning in finance, showing main features and making results more clear for use [36] [10]. Reinforcement learning and new optimization also add to theory by allowing models to learn during change, helping in market ups and downs [7] [43].

Practical Implications

In practice, joining social media sentiment with deep learning makes forecasting stronger which helps investors with better portfolio choice, risk check and early signs of market changes [1] [19] [20]. Multimodal systems that join sentiment, technical signs and macro data create trading systems that can work well in complex markets and improve profit while lowering risk [11] [32] [37]. Sentiment analysis that looks at user impact and unclear sentiment makes signals more useful, helping analysts and decision makers take better steps [16] [31]. Adding XAI makes models more clear, helps follow rules and builds trust by showing how predictions are made [36] [10]. Reinforcement learning models that use sentiment also show value in trading as they create adaptive strategies for volatile markets [7] [43]. But real time use of these models is still hard as they need faster computer systems and better data handling to manage huge and fast social media data [16] [28].

Limitations of the Literature

Even with progress some limits remain. Many studies use only one social media platform or small sets of financial tools, making them less useful in other markets [31] [108] [109] [24]. Many models look only at short term moves, not helping much for long term plans [30] [38] [41] [46]. Deep learning often lacks clarity, making it hard to see what sentiment parts help the result which lowers real use [36] [10]. Accuracy in sentiment classification is not always good as some tools use old lexicons, showing weak results [21] [6] [18] [93]. Markets that change fast also make predictions weak [7] [12] [107]. Social media data has problems like imbalance, noise and spam which make things harder [49] [66] [16]. Research also often studies only a few markets, not all [32] [39] [64]

[98]. Many works do not join data from different sources well which lowers full market view [11] [13] [104] [14]. Also stock coverage is small and computer needs are high, making models less easy to use [34] [35] [84] [29] [16] [105].

Gaps and Future Research Directions

There are still big gaps. We need standard datasets and rules to check models so that results can be compared [19] [5] [57]. Future work should create large datasets from many markets with standard rules for fair use [2] [57]. It is also key to stop noise, spam and wrong info in social media by using GANs or scoring methods to make sentiment more correct [66] [16] [53]. Clarity is also very important. Using SHAP, LIME or other interpretability tools can show which features matter most, building more trust [36] [10] [78]. Time based LSTMs, temporal attention and real time data can make models faster in sudden changes [30] [12] [49]. Sentiment across many languages and markets should be added to make models global and strong [82] [64]. Modeling user impact and social network links can make inputs more real and useful [16] [71]. New fusion methods that join different types of data can also give stronger results [5] [12] [43] [11] [37]. To work better in volatile times, uncertainty models and reinforcement learning are needed [30] [21] [12]. Finally, making models faster and checking their money impact with backtesting will make them more ready for use [16] [43] [2] [57] [99].

Overall Synthesis and Conclusion

The many studies together show that deep learning based social media sentiment analysis has strong power to improve stock forecasting in finance. In many datasets and markets when investor sentiment from social media is added to old financial signs the accuracy becomes better. Advanced models like LSTM types, CNNs, transformers and GNNs catch time patterns, sentiment change and stock links more clearly giving better forecasting than models that only use old price data. Sentiment analysis has also grown. Old lexicon based methods have now been replaced by advanced classifiers like FinBERT and RoBERTa that understand finance language better. Hybrid sentiment models using fuzzy logic, neutrosophic methods and multi lexicons help deal with mixed and unclear social media posts. Adding user influence and credibility makes signals more useful and models more real. Joining many sources like social media, news, technical data and macro data through multimodal systems makes results stronger giving a more full view of stock changes. Still it is hard to mix different data types, remove noise and deal with unstable markets.

Even with growth, clarity of models is still weak, though XAI is helping to make them more clear for investors. Other problems are lack of standard datasets, less work on many languages and uneven tuning which lowers fair checks. Future research must build models that are strong, clear and fast and able to change with market and investor sentiment in real time. Overall deep learning based sentiment analysis has already improved forecasting but its full strength will show when better methods and wider data use are added.

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