International Journal of Scientific Research in Computer Science, Engineering and Information Technology

ISSN : 2456-3307 OPEN ACCESS

Available Online at : www.ijsrcseit.com

doi : https://doi.org/10.32628/CSEIT25112845

Bridging AI and Financial Markets: A Sentiment Analysis Data-Driven Approaches for Stock Market Prediction

Vansh Momaya*[1], Siddharth Hefa[2], Yash Bhate[3], Dr. Nilesh Marathe[1]

*[1]Department of Computer Science Engineering Data Science, D. J. Sanghvi College of Engineering, Mumbai, Maharashtra, India

[2]Department of Electronics & Telecommunications, K J Somaiya College – School of Engineering, Mumbai, Maharashtra, India

[3]Department of Electronics Engineering, VJTI, Mumbai University, Mumbai, Maharashtra, India

ARTICLEINFO

Article History:

Accepted : 14 April 2025

Published: 18 April 2025

Publication Issue

Volume 11, Issue 2

March-April-2025

Page Number

3667-3675

ABSTRACT

The conventional financial value estimating techniques rely primarily on historical stock data, technical indicators, and fundamental parameters, and frequently ignore the psychological and sentiment-driven characters. The most research efforts in ML-based stock prediction models, focusing on decision fusion techniques, hybrid ensemble learning, deep neural networks, and sentiment-aware financial forecasting models. The recently designed time-series predicting models like RNN, CNN, and LSTM show a certain level of accuracy of the model. However, the market trend is influenced by social media mood, price volatility, investors' mentality, and global cues of fiscal markets. Also, Hybrid approaches that collect information from social media platforms like Twitter, Reddit, financial news, and technical indicators have verified superior projecting accuracy than the conventional models that rely only on historical datasets. The decision fusion paradigm has gained traction in stock forecasting, allowing researchers to combine multiple prediction models to enhance forecasting precision. The effectiveness of ensemble learning models, including XGBoost, GBM, and AdaBoost, in stock price forecasting has been widely studied. DL models such as Transformer-based NLP models have further advanced sentiment analysis applications in finance. The ability of BERT to contextualize textual data and extract nuanced financial sentiment has led to significant improvements in sentiment-aware forecasting models. Additionally, Aspect-Based Sentiment Analysis has been employed to disaggregate financial news sentiment, enabling a more granular understanding of investor perceptions and economic events. The review identifies key limitations in current stock forecasting models, including overfitting issues, interpretability concerns, and data scarcity for rare financial events. Additionally, multimodal financial forecasting frameworks integrating textual, numerical, and visual data sources can provide more comprehensive market insights. The adoption of reinforcement learning-based trading strategies, coupled with real-time streaming sentiment analysis, holds significant potential for improving algorithmic trading performance. This paper bridges the gap between machine intelligence research and real-world stock market applications, contributing to the expanding field of AI-driven financial analytics.

Keywords: Stock Market, Machine Learning, Deep Learning, Natural Language Processing, Artificial Intelligence

Introduction

The stock market has become increasingly influenced by factors such as public sentiment and external socio-economic factors due to the proliferation of digital material, social media impacts, and news articles. Due to market volatility, data noise, and unexpected geopolitical or economic disruptions, many DL models require substantial resources and extensive training on huge financial data, limiting their real-time adaptability in high-frequency trading environments. Furthermore, sentiment analysis techniques still struggle with sarcasm, contextual ambiguity, and misinformation, affecting the reliability of sentiment-driven trading strategies [1].

Sentiment analysis has further revolutionized financial forecasting by incorporating real-time investor sentiment extracted from social media platforms, financial news, and public discourse [2]. This transition from rule-based stock prediction to AI-enhanced financial modelling marks a significant shift toward data-centric decision-making in the financial sector. The decision fusion techniques such as majority voting, weighted averaging, stacking, and boosting algorithms have been employed to aggregate predictions from heterogeneous machine learning models, minimizing individual model biases.

AI has redefined financial forecasting by enabling models to self-learn from vast financial datasets and adapt to new market conditions dynamically. Early applications of ML in stock prediction were confined to linear regression models and time-series estimating techniques [3]. While these methods provided reasonable predictions under stable market conditions, they struggled to capture non-linear relationships and high-frequency trading behaviours.

The advent of DL models, such as CNNs, LSTM, and Transformer-based architectures, has enabled AI-driven systems to analyse complex patterns in financial domain [4]. LSTMs, in particular, employed for sequential stock prediction, as they retain memory of past price fluctuations and account for long-term dependencies in financial data. Recent studies indicate that hybrid models combining LSTMs with sentiment analysis techniques outperform traditional ML models, providing more accurate and context-aware financial forecasts [5].

Investor sentiment plays a key role in stock price variations, particularly in an era where social media and digital news platforms drive market behaviour. Traditional stock prediction models often ignore the psychological and emotional dimensions influencing market trends. Sentiment analysis techniques categorize financial news and investor discussions into positive, negative, or neutral sentiments, thereby allowing predictive models to gauge market optimism or pessimism. Research findings indicate that negative sentiment trends often precede stock market downturns, while positive sentiment correlates with bullish trends [9].

Studies integrating BERT-based sentiment classifiers with LSTM-driven stock price models have demonstrated notable reductions in prediction errors, reinforcing the value of NLP-driven insights in stock market forecasting. The application of Transformer-based NLP models, such as BERT and GPT (Generative Pre-trained Transformer), has further enhanced the precision of financial sentiment classification. These models are capable of context-aware sentiment interpretation, improving the reliability of sentiment-driven stock prediction models. However, challenges such as sarcasm detection, misinformation filtering, and sentiment amplification biases remain key hurdles in developing fully automated sentiment-based trading strategies [10].

LITERATURE REVIEW

Recent advances in NLP and DL have fostered a growing body of research into sentiment analysis can significantly enhance the predictive performance of stock price models. Chou et al. [1] employed LSTM networks integrated with sentiment analysis utilizing a two-year dataset comprising stock prices and sentiment-laden news articles sourced from Yahoo Finance. However, the study was constrained by a limited dataset size and the exclusion of real-time forecasting capabilities. Similarly, Batra and Daudpota [2] integrated StockTwits sentiment with predictive modelling to reflect real-time market perceptions, showing improved movement predictions.

Recent works have also explored the fusion of heterogeneous models for sentiment extraction. Sadr et al. [4] proposed a deep network architecture, emphasizing the benefits of hybrid feature representations. Momaya et al. (2023) [5] compared LSTM and GRU networks and found that GRU slightly outperformed LSTM in terms of training efficiency and model convergence. Moreover, Tam et al. [6] introduced ConvBiLSTM, a combination of convolutional and bidirectional LSTM layers, demonstrating superior classification accuracy in sentiment-laden texts.

While numerous studies affirm the efficacy of sentiment-aware models, challenges remain in terms of generalization, interpretability, and robustness under extreme market volatility. Budiharto [9] and Peivandizadeh et al. (2024) [10], focused on regional implementations and incorporated social sentiment with models like transductive LSTM. The application of generative models and transfer learning also presents a growing trend. Peivandizadeh et al. [10] employed transductive LSTM combined with social media sentiment to enhance generalization capabilities in price forecasting. These studies offered contextual depth but called for broader validation across indices and real-time markets.

Beyond traditional sentiment classification, researchers have ventured into fine-grained and aspect-based sentiment analysis. Xue and Li [11] introduced gated convolutional networks for aspect-based sentiment detection, allowing for more nuanced sentiment interpretation in multi-topic documents. Furthermore, Lou (2023) [12] and Zhu and Yen (2024) [13] leveraged fine-tuned BERT and BERTopic clustering respectively, to classify market sentiment and evaluate predictive robustness through back testing, and marking progress in accuracy but still demanding high computational cost and robustness in evaluation.

A few studies, such as Abid et al. (2019) [14] and Darapaneni et al. (2022) [15], explored hybrid CNN-RNN structures and India-specific datasets. These emphasized local effectiveness but suffered from global applicability. Multi-source learning, explored by Zhang et al. (2018) [16], also lacked real-time deployment and strong feature selection. Foundational ML applications, like those of Mankar et al. (2018) [17], revealed the importance of integrating deep learning and refined features. Stock price prediction models have increasingly incorporated multimodal data sources, demonstrating that combining textual and numerical indicators yields more robust predictions.

Innovative frameworks by Cicekyurt and Bakal (2025) [18], and Arratia et al. (2021) [19], displayed strong transfer learning performance and statistical insight but were limited by language diversity and predictive automation. In parallel, Zhao et al. (2023) [20] and Chen et al. (2025) [21] explored adopted multi-model fusion with transfer learning, achieving improved sentiment extraction across domains and bibliometric review respectively, underscoring the need for model simplification and empirical testing.

Further studies extended to neural networks, (Arauco Ballesteros et al., 2024) [22] proposed an ensemble model using fundamental, technical, and sentiment-based features, social network integration (Huang et al., 2023) [23], and regional modeling in Vietnam (Phuoc et al., 2024) [24], each contributing unique angles yet requiring broader applicability and real-time relevance. LSTM-based sentiment prediction (Bacco et al., 2024) [25] and trading strategies with sentiment (Li et al., 2024) [26] emphasized robustness but lacked live market simulation. Recent innovations in federated learning (Sakhare & Shaik, 2024) [27] and ESG sentiment with BERT (Dorfleitner & Zhang, 2024) [28] reflect cutting-edge developments. However, these remain either experimental or computationally intensive, warranting optimization and real-world validation. Furthermore, recent efforts have turned toward federated learning [27], ESG sentiment [28], and knowledge transfer [18] to tackle data privacy, ethical considerations, and domain adaptation.

Despite the progress, literature calls for deeper exploration into domain-specific language models, contextualized sentiment interpretation, and the integration of explainable AI (XAI) frameworks to build trust in sentiment-driven financial forecasting systems. Thus, Traditional ML models (SVM, Random Forest, Logistic Regression) are easier to interpret but struggle with complex sentiment nuances. Deep Learning models (LSTM, BERT, CNNs) have high accuracy but suffer from high computational costs and lack real-time implementation. Hybrid approaches (BERTopic + DL [13], ConvBiLSTM [6], Fusion Learning) show promise but require more validation across different datasets. Many studies focus on specific regions and need broader applicability for global financial markets. Lack of real-time prediction models is a common research gap across multiple studies.

METHODOLOGY

The adopted methodology leverages a comprehensive fusion of sentiment analysis and financial analytics to forecast stock market trends, integrating principles from behavioural finance and the Efficient Market Hypothesis.

A. Data Sources

To build a robust stock prediction model, data should be collected from diverse sources, A multi-source data strategy is employed, historical stock prices (e.g., Yahoo Finance, Google Finance, Alpha Vantage), social media sentiment (e.g., Twitter, Reddit, StockTwits), financial news & reports (e.g., Bloomberg, Reuters, SEC filings), macroeconomic indicators (e.g., GDP, inflation rates, crude oil prices), ensuring a holistic sentiment and market representation.

B. Data Preprocessing

Data preprocessing is a critical step in sentiment-aware stock market prediction, ensuring that both structured financial data and unstructured textual inputs are transformed into a consistent, meaningful format suitable for modelling. Missing data is handled through interpolation, mean imputation, or predictive modelling techniques to maintain dataset integrity.

Textual data undergoes thorough preprocessing using standard NLP techniques such as tokenization, stopword removal, and lemmatization, along with Named Entity Recognition (NER) to identify company-specific mentions. Sentiment is quantified through a hybrid of lexicon-based (e.g., VADER, Loughran-McDonald) [22] and machine learning-based models to assess the polarity and intensity of discourse.

Feature engineering encompasses both textual and financial indicators, including polarity scores, emotional tone, word embeddings (e.g., TF-IDF, Word2Vec, BERT [13]), as well as price-based metrics like volatility and trading volume. These features are statistically correlated with stock movements to affirm their predictive significance.

C. Model Selection and Implementation

The model architecture integrates both traditional machine learning classifiers (e.g., Logistic Regression [3], Random Forest [16]) and advanced deep learning techniques (e.g., LSTM [9], GRU [5], BERT/FinBERT), allowing for temporal and semantic pattern recognition. Ensemble learning is further incorporated to bolster robustness and generalization.

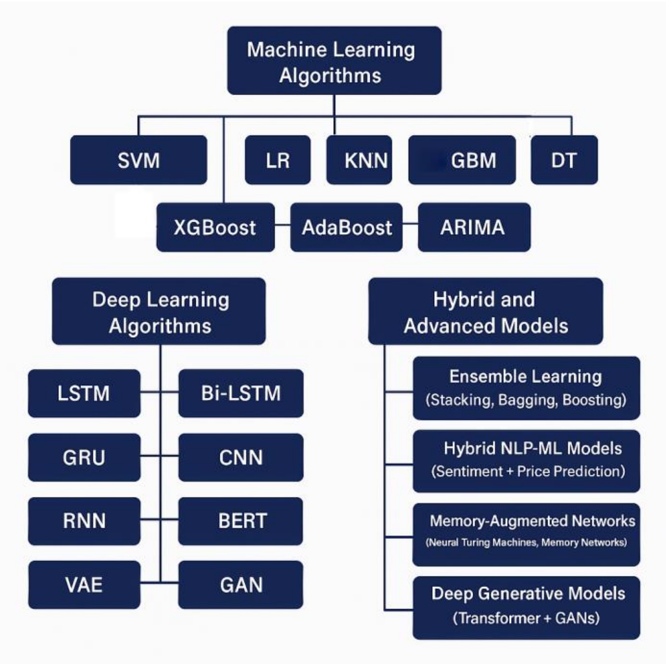

Figure 1. Model Classification

D. Performance Metrices

Evaluation is conducted using classification metrics (Accuracy, Precision, Recall, F1-score, RMSE) and financial benchmarks (Sharpe Ratio, ROI), facilitating both technical accuracy and practical applicability through simulated trading scenarios.

RESULT DISCUSSION

Recent advancements in sentiment-aware financial forecasting underscore the growing efficacy of both traditional ML and contemporary DL models. The traditional ML models like RF, LR, and SVM [17], while generally exhibiting lower predictive accuracy (ranging from 75% to 85%), still maintain competitive precision and recall scores in environments constrained by computational resources or smaller datasets. Among these, Random Forests showed relatively better generalization with accuracy approaching 85% and AUC scores around 0.82.

Conversely, Comparative analysis reveals that Deep Learning approaches, particularly fine-tuned BERT, ConvBiLSTM [6], and LSTM [10], consistently outperform classical ML algorithms across standard evaluation metrics. Fine-tuned BERT [28] models have demonstrated the highest overall performance, achieving accuracy levels between 90% and 93% with a corresponding F1-score and AUC close to 0.91 and 0.94, respectively, highlighting their robust ability to understand contextual sentiment in textual data.

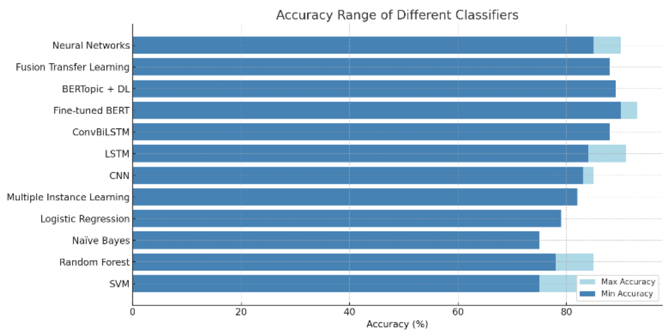

Figure 2. Comparative Analysis

Additionally, hybrid and transfer learning-based models, such as Fusion Transfer Learning [20] and BERTopic-integrated [13] DL frameworks, have emerged as effective solutions, achieving performance metrics comparable to high-end DL models while offering improved model interpretability and domain adaptability. These approaches present a promising direction for future work, especially in scenarios requiring integration of topic modelling with sentiment classification. Further research is warranted to address challenges in explainability and real-time deployment of these complex architectures.

TABLE I CLASSIFIER WITH PERFORMANCE ACCURACY

Classifier	Citation	Accuracy
SVM	[2], [17]	75%-82%
Random Forest	[2], [16], [17]	78%-85%
Naïve Bayes	[11]	75%
Logistic Regression	[3]	79%
Multiple Instance Learning	[16]	82%
CNN	[4], [14]	83%-85%
LSTM	[1], [5], [6], [9], [10], [15], [25]	84%-91%
ConvBiLSTM	[6]	88%
Fine-tuned BERT	[12], [18], [28]	90%-93%
BERTopic + DL	[13]	89%
Fusion Transfer Learning	[20]	88%
Neural Networks	[7], [22]	85%-90%

Data in artificial intelligence exists in various modalities, including text, image, video, and audio, each requiring specific analytical techniques. The comparative sentiment distribution analysis reveals that financial news datasets typically exhibit a more balanced distribution across sentiment classes. For instance, the Reuters Financial News and Bloomberg Market Sentiment datasets display an even allocation of data points among the five sentiment categories, reflecting the relatively objective and informative nature of journalistic reporting.

Conversely, social media datasets, such as those from Twitter, Reddit WallStreetBets, and StockTwits, are characterized by sentiment polarity extremes, particularly in the "Strongly Positive" and "Strongly Negative" classes. This skewness is attributed to user-generated content and speculative commentary, which are often emotionally charged and biased.

In contrast, corporate reporting datasets, such as SEC Filings (10-K, 10-Q) and S&P 500 Earnings Reports, display a higher prevalence of neutral sentiment, consistent with their focus on factual, regulated disclosures and performance metrics. These documents are structured and adhere to compliance standards, resulting in fewer subjective expressions.

Overall, this summary highlights the heterogeneity across financial text sources and underscores the importance of dataset selection based on research objectives, whether the aim is to capture speculative sentiment, journalistic tone, or factual financial performance. This diversity also signals the need for domain-adaptive sentiment models capable of handling varied linguistic styles and sentiment intensities.

RESEARCH GAP

The most common research gaps are: Real-time processing, model interpretability, and computational efficiency remain critical gaps. Most models are designed for specific stock exchanges and fail to generalize across global markets. Hybrid approaches integrating fundamental analysis, technical indicators, and alternative data sources are underexplored. Financial market manipulation detection using sentiment analysis needs more research.

TABLE II RESEARCH GAPS IN EXISTING SYSTEMS

Research Gap Category	Description	References
Lack of Real-Time Sentiment Analysis	Most models rely on historical data rather than real-time sentiment updates, limiting practical trading	[1], [7], [10], [12], [13], [26]

Research Gap Category	Description	References
	applications.	
Limited Generalization Across Markets	Many studies focus on specific stock exchanges (e.g., S&P 500, Indian Market, Vietnam Market), making the models less generalizable.	[9], [15], [24], [25]
High Computational Cost of Deep Learning Models	Transformer-based models (BERT, FinBERT, LSTM) require significant computational resources, making real-time processing difficult.	[4], [6], [12], [18], [20]
Lack of Explainability and Interpretability	Deep learning models often function as black-box solutions, reducing trust in financial decision-making.	[7], [8], [14], [22]
Need for Hybrid Models	Combining sentiment with technical & fundamental indicators is underexplored. Most studies use sentiment analysis in isolation.	[5], [9], [17], [19], [21]
Limited Focus on Multimodal Data (Text, Image, Video)	Most studies analyze only text-based sentiment, neglecting financial videos, social media images, and investor behavior analysis.	[11], [13], [16], [23]
Insufficient Back-testing & Validation on Live Markets	Many models demonstrate high accuracy on historical data but lack proper validation in live market scenarios.	[12], [19], [20], [26]
Overfitting Issues in Neural Networks	Many DL models perform well on training dataset but fail to simplify unseen data.	[7], [9], [22], [25]
Security & Privacy Issues in Sentiment Analysis (Blockchain, Federated Learning)	Blockchain-based or federated learning techniques remain under-researched for privacy-preserving financial sentiment analysis.	[27]
Underutilization of Alternative Data Sources (Google Trends, Reddit, ESG)	Most studies rely on Twitter & news data while ignoring alternative data sources like ESG reports, Google Trends, and Reddit.	[8], [14], [19], [28]
Lack of Cross-Language Financial Sentiment Analysis	Most sentiment analysis models focus on English-language datasets, with little attention given to multilingual stock market sentiment.	[18], [22], [23]
Market Manipulation Detection	Current sentiment analysis models fail to differentiate between organic sentiment shifts and manipulative practices like "pump-and-dump" schemes.	[3], [6], [20], [24]

CONCLUSION

The future trajectory of stock market forecasting is poised to be transformed by hybrid, AI-driven trading systems that integrate advanced methodologies such as deep learning, reinforcement learning, sentiment-aware NLP, and decentralized federated learning. The implementation of ML and DL algorithms is anticipated to mitigate existing challenges in the domain, thereby enhancing predictive accuracy, ensuring real-time adaptability, and improving the interpretability of financial analytics. Over recent years, the field of stock market prediction has undergone substantial evolution, with ML, DL, and NLP techniques, particularly sentiment-aware and multi-modal approaches, offering powerful tools for anticipating market dynamics. The fusion of multi-source datasets, hybrid ensemble learning models, and sentiment-driven NLP has yielded improved forecasting performance. Nonetheless, persisting challenges such as model transparency, data bias, and computational complexity remain areas of concern. As artificial intelligence continues to progress, the development of next-generation financial prediction models will require the integration of real-time analytics, decision fusion mechanisms, and explainable AI (XAI) frameworks to foster greater market reliability and investor confidence. This study endeavours to bridge the gap among academic inquiry and actual financial applications by synthesizing current advancements in ensemble learning, sentiment-based modelling, and decision-level integration, ultimately establishing a robust foundation for future research and innovation in AI-empowered financial analytics.

References

[1]. C. Chou, J. Park, and E. Chou, "Predicting Stock Closing Price After COVID-19 Based on Sentiment Analysis and LSTM," IEEE, 2021. doi: 10.1109/IAEAC50856.2021.9390845.

[2]. R. Batra and S. M. Daudpota, "Integrating StockTwits with Sentiment Analysis for Better Prediction of Stock Price Movement," IEEE, 2018. doi: 10.1109/ICOMET.2018.8346382.

[3]. T. H. Ly and K. Nguyen, "Do Words Matter: Predicting IPO Performance from Prospectus Sentiment," IEEE, 2020. doi: 10.1109/ICSC.2020.00061.

[4]. H. Sadr, M. M. Pedram, and M. Teshnehlab, "Multi-view Deep Network: A Deep Model Based on Learning Features from Heterogeneous Neural Networks for Sentiment Analysis," IEEE Access, 2020. doi: 10.1109/ACCESS.2020.9085370.

[5]. H. Momaya, V. Patel and V. Momaya, "Forecasting of Stock Trend and Price using Machine Intelligence LSTM and GRU Models", IEEE Access, 2023. doi: 10.1109/ViTECoN58111.2023.10157684

[6]. S. Tam, R. B. Said, and Ö. Ö. Tanriöver, "A ConvBiLSTM Deep Learning Model-Based Approach for Twitter Sentiment Classification," IEEE Access, 2021. doi: 10.1109/ACCESS.2021.3064830.

[7]. J. Shen and M. O. Shafiq, "Short-term Stock Market Price Trend Prediction Using a Comprehensive Deep Learning System," J. Big Data, vol. 7, no. 1, 2020. doi: 10.1186/s40537-020-00333-6.

[8]. N. Rouf et al., "Stock Market Prediction Using Machine Learning Techniques: A Decade Survey on Methodologies, Recent Developments, and Future Directions," Electronics, vol. 10, no. 21, 2021. doi: 10.3390/electronics10212717.

[9]. W. Budiharto, "Data Science Approach to Stock Prices Forecasting in Indonesia During Covid-19 Using Long Short-Term Memory (LSTM)," J. Big Data, 2021. doi: 10.1186/s40537-021-00430-0.

[10]. A. Peivandizadeh et al., "Stock Market Prediction With Transductive Long Short-Term Memory and Social Media Sentiment Analysis," IEEE Access, 2024. doi: 10.1109/ACCESS.2024.3399548.

[11]. W. Xue and T. Li, "Aspect Based Sentiment Analysis with Gated Convolutional Networks," arXiv preprint, 2018. doi: 10.48550/arXiv.1805.07043.

[12]. J. Lou, "Stock Market Sentiment Classification and Backtesting via Fine-tuned BERT," arXiv preprint, 2023. doi: 10.48550/arXiv.2309.11979.

[13]. E. Zhu and J. Yen, "BERTopic-Driven Stock Market Predictions: Unraveling Sentiment Insights," arXiv preprint, 2024. doi: 10.48550/arXiv.2404.02053.

[14]. F. Abid et al., "Sentiment Analysis Through Recurrent Variants Latterly on Convolutional Neural Network of Twitter," Future Generation Comput. Syst., vol. 95, pp. 292–302, 2019. doi: 10.1016/j.future.2018.12.018.
[15]. N. Darapaneni et al., "Stock Price Prediction Using Sentiment Analysis and Deep Learning for Indian Markets," arXiv preprint arXiv:2204.05783, 2022. doi: 10.48550/arXiv.2204.05783.
[16]. X. Zhang et al., "Stock Market Prediction via Multi-Source Multiple Instance Learning," IEEE Access, 2018. doi: 10.1109/ACCESS.2018.2869735.
[17]. T. Mankar et al., "Stock Market Prediction Based on Social Sentiments Using Machine Learning," IEEE, 2018. doi: 10.1109/ICSCET.2018.8537242.
[18]. E. Cicekyurt and G. Bakal, "Enhancing Sentiment Analysis in Stock Market Tweets Through BERT-Based Knowledge Transfer," Comput. Econ., 2025. doi: 10.1007/s10614-025-10901-8.
[19]. A. Arratia et al., "Sentiment Analysis of Financial News: Mechanics and Statistics," in Springer, 2021. doi: 10.1007/978-3-030-66891-4_9.
[20]. Z. Zhao, W. Liu, and K. Wang, "Research on Sentiment Analysis Method of Opinion Mining Based on Multi-Model Fusion Transfer Learning," J. Big Data, 2023. doi: 10.1186/s40537-023-00837-x.
[21]. X. Chen et al., "Sentiment Analysis for Stock Market Research: A Bibliometric Study," Natural Language Process. J., 2025. doi: 10.1016/j.nlp.2025.100125.
[22]. M. A. Arauco Ballesteros and E. A. Martínez Miranda, "Stock Market Forecasting Using a Neural Network Through Fundamental Indicators, Technical Indicators, and Market Sentiment Analysis," Comput. Econ., 2024. doi: 10.1007/s10614-024-10711-4.
[23]. J. Y. Huang, C. L. Tung, and W. Z. Lin, "Using Social Network Sentiment Analysis and Genetic Algorithm to Improve the Stock Prediction Accuracy of the Deep Learning-Based Approach," Int. J. Comput. Intell. Syst., 2023. doi: 10.1007/s44196-023-00276-9.
[24]. T. Phuoc et al., "Applying Machine Learning Algorithms to Predict the Stock Price Trend in the Stock Market – The Case of Vietnam," Humanit. Soc. Sci. Commun., 2024. doi: 10.1057/s41599-024-02807-x.
[25]. L. Bacco et al., "Investigating Stock Prediction Using LSTM Networks and Sentiment Analysis of Tweets Under High Uncertainty: A Case Study of North American and European Banks," IEEE Access, 2024. doi: 10.1109/ACCESS.2024.3450311.
[26]. M. Li et al., "An Interval Constraint-Based Trading Strategy with Social Sentiment for the Stock Market," Financ. Innov., 2024. doi: 10.1186/s40854-023-00567-2.
[27]. N. N. Sakhare and I. S. Shaik, "Spatial Federated Learning Approach for the Sentiment Analysis of Stock News Stored on Blockchain," Spat. Inf. Res., 2024. doi: 10.1007/s41324-023-00529-x.
[28]. G. Dorfleitner and R. Zhang, "ESG News Sentiment and Stock Price Reactions: A Comprehensive Investigation via BERT," Schmalenbach J. Bus. Res., 2024. doi: 10.1007/s41471-024-00185-3.