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Enhancing Stock Price Prediction through Sentiment Analysis: A Comparative Study of Machine Learning and Deep Learning Models Using Financial News Data

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A B S T R A C T

This study explores the use of machine learning (ML) and deep learning (DL) models for predicting stock price movements through sentiment analysis of financial news articles. Four models were evaluated: Random Forest (RF), Gradient Boosting (GB), Long Short-Term Memory (LSTM), and Bidirectional Encoder Representations from Transformers (BERT). The results showed that deep learning models, particularly BERT, outperformed traditional ML models, achieving higher accuracy, precision, recall, and F1 scores. BERT's ability to capture contextual relationships in text proved superior in handling the complexities of financial news. This research highlights the effectiveness of sentiment analysis in stock market prediction and suggests that advanced ML and DL techniques can enhance forecasting accuracy. Future work could focus on refining these models by integrating more data sources and exploring hybrid approaches.

Keywords: Stock price prediction, sentiment analysis, machine learning, deep learning, BERT, LSTM, financial news.

INTRODUCTION

The relationship between sentiment analysis and financial markets has garnered considerable attention in recent years, particularly in the context of predicting stock price movements. Investors and financial analysts have long relied on news articles, social media, and other textual sources to gauge public sentiment and forecast market trends. The integration of machine learning (ML) and deep learning (DL) techniques into sentiment analysis has revolutionized how financial data is processed and analyzed. Advancements in natural language processing (NLP) have enabled models to understand and extract meaningful insights from large volumes of unstructured text data, leading to more accurate predictions of stock prices (Kou et al., 2022).

Recent studies have demonstrated that sentiment extracted from news articles, social media posts, and even financial reports can serve as a valuable predictor for stock price movements (Zhang et al., 2018). By analyzing the sentiment of financial news, investors can gain insights into market trends, which can inform trading decisions and investment strategies. This research explores the effectiveness of various machine learning and deep learning models in analyzing sentiment and predicting stock price movements. Models such as Random Forest (RF), Gradient Boosting (GB), Long Short-Term Memory (LSTM), and Transformer-based models, including Bidirectional Encoder Representations from Transformers (BERT), are evaluated in terms of their accuracy and predictive power.

The objective of this study is to conduct a comparative analysis of these models and determine which one provides the most accurate predictions for stock price movements based on sentiment. The models are assessed using various performance metrics, including accuracy, precision, recall, F1-score, and Mean Squared Error (MSE). This paper provides insights into the relative strengths and weaknesses of each model and offers guidance for future applications of sentiment analysis in the financial domain.

LITERATURE REVIEW

The application of machine learning and deep learning techniques to sentiment analysis in financial markets has been a subject of extensive research. Several studies have shown that sentiment analysis plays a critical role in predicting market movements by leveraging unstructured data such as news articles, social media content, and financial reports (Bollen et al., 2011; Liao & Zhou, 2019). According to Zhang et al. (2018), the combination of sentiment analysis with stock price prediction can significantly enhance the accuracy of predictions, as it allows for the incorporation of public sentiment, which is a critical driver of stock market behavior.

Traditional machine learning models, such as Random Forest and Gradient Boosting, have been widely used for sentiment analysis in the financial sector. Random Forest, a popular ensemble learning method, has demonstrated its ability to handle high-dimensional data and deliver robust predictions (Breiman, 2001). Several studies have applied Random Forest to stock price prediction and found it to be effective in terms of accuracy and stability, though its performance tends to be limited when dealing with complex sequential dependencies (Kim & Lee, 2017). Gradient Boosting, another ensemble learning technique, has shown strong performance in predictive tasks due to its ability to model complex relationships between features (Chen & Guestrin, 2016). However, like Random Forest, it may struggle to fully capture temporal dependencies in financial data, which is crucial for stock price prediction.

In contrast, deep learning models, particularly Long Short-Term Memory (LSTM) networks, have become increasingly popular for analyzing sequential data, including stock market time-series data. LSTM networks, a type of recurrent neural network (RNN), are designed to capture long-range dependencies in sequential data, making them well-suited for time-series forecasting (Hochreiter & Schmidhuber, 1997). Numerous studies have applied LSTM networks to financial forecasting tasks, demonstrating their ability to predict stock price movements with higher accuracy than traditional machine learning models (Xie et al., 2020). LSTM's ability to learn from historical data allows it to model temporal patterns in stock prices, which are often influenced by past market trends.

Transformer-based models, such as BERT, have revolutionized the field of natural language processing by providing state-of-the-art performance on various NLP tasks (Devlin et al., 2019). BERT, specifically designed to understand contextual relationships within text, has proven to be highly effective in sentiment analysis tasks. By capturing both global and local contexts in text, BERT can extract nuanced sentiment features from financial news articles and social media posts. Several studies have demonstrated the superior performance of BERT over traditional machine learning models and even LSTM in sentiment analysis for stock market prediction (Yang et al., 2021; Sun et al., 2022). BERT's ability to handle large-scale, domain-specific datasets allows for more accurate sentiment extraction and, consequently, better stock price predictions.

Recent comparative studies have focused on evaluating the performance of machine learning and deep learning models in financial sentiment analysis. For example, a study by Ghosh and Gupta (2020) compared traditional machine learning models such as SVM and Random Forest with deep learning models like LSTM and BERT for stock market prediction. The results indicated that deep learning models, particularly BERT, outperformed traditional machine learning models in terms of prediction accuracy and ability to capture the complex nature of financial data. Similarly, Zhang et al. (2022) found that combining sentiment analysis with deep learning models like LSTM and BERT led to more accurate predictions compared to traditional methods.

In conclusion, while traditional machine learning models have proven effective in financial sentiment analysis, deep learning models, particularly LSTM and BERT, offer superior performance due to their ability to handle sequential data and capture contextual relationships in text. This study aims to further explore and compare these models, with the goal of determining which one provides the most accurate predictions for stock price movements based on sentiment analysis.

METHODOLOGY

Data Collection

To analyze the sentiment of banking news and its impact on stock prices, data was collected from multiple sources, ensuring a diverse and comprehensive dataset. The primary sources included financial news websites, social media platforms, and official press releases from banking institutions. Financial news articles were gathered using web scraping tools and APIs from sources like Reuters, Bloomberg, and Financial Times. These articles focused on topics such as banking operations, policy changes, mergers and acquisitions, and macroeconomic factors affecting the financial sector.

Social media platforms, including Twitter and Reddit, were leveraged to capture real-time public opinion on banking events. For this, advanced scraping and API tools were employed to extract relevant posts containing hashtags and keywords associated with major banking institutions and financial developments. Social media data was enriched by filtering posts for relevance using natural language processing (NLP) techniques.

Historical stock price data was sourced from well-known financial databases such as Bloomberg, Yahoo Finance, and Quandl. This data included daily opening and closing prices, high and low prices, trading volumes, and other technical indicators. The stock price data was specifically aligned with the dates and times of the collected news and social media posts to facilitate accurate correlation analysis.

In addition to these primary sources, press releases from official bank websites were collected to provide context for significant financial events. These press releases were downloaded and stored in a structured format for easy integration with other datasets.

Below is an overview of the dataset

Dataset Component	Source	Volume	Time Period
Financial News	Financial Times, Reuters, Bloomberg	5000 articles	Jan 2020 – Dec 2024
Social Media Posts	Twitter, Reddit	1000 posts	Jan 2020 – Dec 2024
Stock Price Data	Bloomberg, Yahoo Finance	2000 records	Jan 2020 – Dec 2024
Press Releases	Official Bank Websites	1000 documents	Jan 2020 – Dec 2024

This rich and diverse dataset forms the foundation for robust sentiment analysis and the exploration of its impact on stock price movements.

Data Preprocessing

The data preprocessing stage was critical to ensure the quality, consistency, and reliability of the collected data. Textual data, including news articles, social media posts, and press releases, underwent a series of cleaning and transformation steps. Initially, the data was stripped of special characters, HTML tags, and stop words to remove irrelevant content. For social media posts, additional filters were applied to exclude spam, advertisements, and unrelated posts. Tokenization was then used to split text into individual words or phrases, and lemmatization was performed to convert words to their root forms, reducing redundancy and dimensionality.

Sentiment labels were assigned to the textual data using both lexicon-based and machine learning-based approaches. Lexicon-based methods utilized predefined dictionaries of positive and negative words to score sentiment, while machine learning models such as logistic regression and BERT-based classifiers were trained on annotated financial datasets to predict sentiment polarity. For stock price data, preprocessing involved addressing missing values and ensuring temporal alignment. Missing values were imputed using techniques such as forward-fill and backward-fill, depending on the nature of the data. Outliers were identified and handled using statistical methods like the interquartile range (IQR) to prevent skewed results. All timestamps were standardized to Coordinated Universal Time (UTC) to ensure consistent mapping between sentiment data and stock prices.

Further, normalization techniques were applied to numerical data, such as stock prices and trading volumes, to bring all features to a comparable scale. Time-series transformations, including log transformations and differencing, were implemented to stabilize trends and eliminate seasonality from the data. The data was subsequently split into training, validation, and testing sets. To maintain a balanced distribution of sentiment classes, stratified sampling was employed. The training set was augmented using techniques like synonym replacement and back-translation to improve the diversity of textual data, enhancing the model's ability to generalize across different contexts.
Finally, all processed data was stored in structured formats, such as CSV and database systems, for easy access and integration during the modeling phase. This comprehensive preprocessing pipeline ensured the readiness of the data for subsequent feature extraction and modeling tasks.

Feature Selection

Feature selection played a pivotal role in enhancing the model's predictive accuracy and reducing computational complexity. For textual data, features such as term frequency-inverse document frequency (TF-IDF), sentiment polarity scores, and pre-trained word embeddings (e.g., Word2Vec, GloVe, and FastText) were extracted. These features captured the semantic and syntactic nuances of the text, enabling the model to understand both explicit and implicit sentiment cues. Advanced NLP techniques, such as topic modeling using Latent Dirichlet Allocation (LDA), were employed to identify prevalent themes in the data, which were then included as additional features.

For numerical data, including stock prices and trading volumes, various statistical and technical indicators were calculated. Features like moving averages, relative strength index (RSI), Bollinger Bands, and MACD (Moving Average Convergence Divergence) provided insights into market trends and volatility. Lagged features were introduced to capture temporal dependencies, while interaction features, combining sentiment polarity with technical indicators, were engineered to reflect the interplay between market sentiment and stock performance.

Feature importance was assessed using advanced algorithms like Random Forest, Gradient Boosting, and SHAP (SHapley Additive exPlanations) values. Recursive Feature Elimination (RFE) was conducted to iteratively remove less significant features, ensuring that only the most impactful variables were retained. Principal Component Analysis (PCA) was also applied to reduce dimensionality while preserving the variance in the dataset, further enhancing the computational efficiency and robustness of the model.

Feature Engineering

Feature engineering was a critical step in transforming raw data into a format suitable for predictive modeling. For textual data, sentiment scores were aggregated daily to compute average sentiment trends over time. Additional features, such as the sentiment volatility index, were engineered to quantify sudden changes in public opinion. Temporal features, such as day-of-week and month-of-year indicators, were added to capture seasonality in sentiment and stock price movements.

To capture the interaction between textual sentiment and numerical data, composite features were created by combining sentiment polarity with trading volume and stock price changes. These features provided a nuanced understanding of how sentiment influenced market behavior under different conditions. Time-series-specific transformations, such as rolling averages and exponential smoothing, were applied to stabilize the data and highlight long-term trends.

Advanced text representation methods, including transformer-based embeddings from models like BERT and GPT, were utilized to generate context-aware feature vectors. These embeddings captured the contextual relationships between words, phrases, and sentences, improving the model's ability to understand complex financial narratives. Additionally, custom lexicons tailored to the financial domain were developed to enhance sentiment analysis accuracy, particularly for industry-specific jargon and phrases.

For numerical features, engineered metrics such as price momentum, volatility clustering, and liquidity ratios were incorporated to provide deeper insights into market dynamics. Ensemble techniques, combining multiple feature sets, were employed to leverage the strengths of different feature types, ensuring a holistic representation of the data.

By integrating these advanced feature selection and engineering techniques, the methodology ensured the development of a robust and highly predictive model capable of accurately capturing the relationship between banking news sentiment and stock price movements.

Fine-Tuning

Fine-tuning was implemented to optimize the performance of the predictive models and ensure their alignment with the objectives of the analysis. Initially, pre-trained models such as BERT, GPT, and transformer-based architectures were adapted to the financial domain through domain-specific fine-tuning. This involved training the models on financial news datasets, enabling them to grasp industry-specific terminology and context.

Hyperparameter optimization was conducted using techniques like grid search and Bayesian optimization to determine the best combination of parameters, including learning rates, batch sizes, and the number of epochs. Cross-validation was employed during fine-tuning to evaluate model performance on unseen data and prevent overfitting. Advanced regularization techniques, such as dropout and weight decay, were also applied to enhance generalization.
Transfer learning strategies were utilized to leverage knowledge from general-purpose language models, reducing the need for extensive labeled data. Domain-specific adaptations, such as augmenting sentiment polarity detection with custom lexicons and integrating financial event-specific features, further enhanced model accuracy.

Iterative feedback loops, incorporating performance metrics and error analysis, were established to refine the models continuously. By identifying areas where predictions deviated from actual outcomes, adjustments were made to the feature set, model architecture, and training data. This iterative fine-tuning process ensured that the models were both accurate and reliable in capturing the nuanced relationship between sentiment and stock price dynamics.

Model Evaluation

To evaluate the effectiveness of the sentiment analysis model and its impact on stock price prediction, several machine learning and deep learning models were employed. These included Random Forest, Gradient Boosting Machines, Long Short-Term Memory (LSTM) networks, and Transformer-based architectures like BERT. Each model was trained and validated using the preprocessed data.

Performance metrics such as accuracy, precision, recall, F1-score, and mean squared error (MSE) were used to assess classification and regression tasks, respectively. Cross-validation techniques were implemented to ensure the robustness of results, and hyperparameter tuning was conducted using grid search and Bayesian optimization to maximize model performance.
The final evaluation involved comparing the model's predictions against actual stock price movements to determine the impact of sentiment on market behavior. Visualization techniques, such as time-series plots and correlation heatmaps, were used to interpret the results and validate the model's findings.

This methodology ensures a systematic and comprehensive approach to understanding the relationship between banking news sentiment and stock price dynamics, leveraging cutting-edge machine learning techniques and rigorous evaluation processes.

RESULTS

In this section, we present the results obtained from applying various machine learning and deep learning models to analyze the relationship between sentiment extracted from financial news and social media posts and stock price movements. The goal is to assess how well sentiment analysis correlates with stock price dynamics and determine which model provides the most accurate predictions.
The models under evaluation include traditional machine learning algorithms such as Random Forest and Gradient Boosting, as well as deep learning models like Long Short-Term Memory (LSTM) networks and Transformer-based architectures, including BERT. These models were selected based on their ability to handle complex relationships within both textual and numerical data.

Model Performance Metrics

To assess the effectiveness of the models, we utilized various performance metrics, including accuracy, precision, recall, F1-score for classification tasks, and Mean Squared Error (MSE) for regression tasks. Cross-validation was used to ensure the robustness of the model evaluations. The following table summarizes the performance of each model based on these metrics.

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	MSE (Mean Squared Error)
Random Forest	85.4	82.3	88.1	85.1	0.022
Gradient Boosting	87.2	84.7	90.4	87.5	0.018
Long Short-Term Memory (LSTM)	90.3	88.6	91.7	90.1	0.015
BERT	91.6	90.2	93.5	91.8	0.014

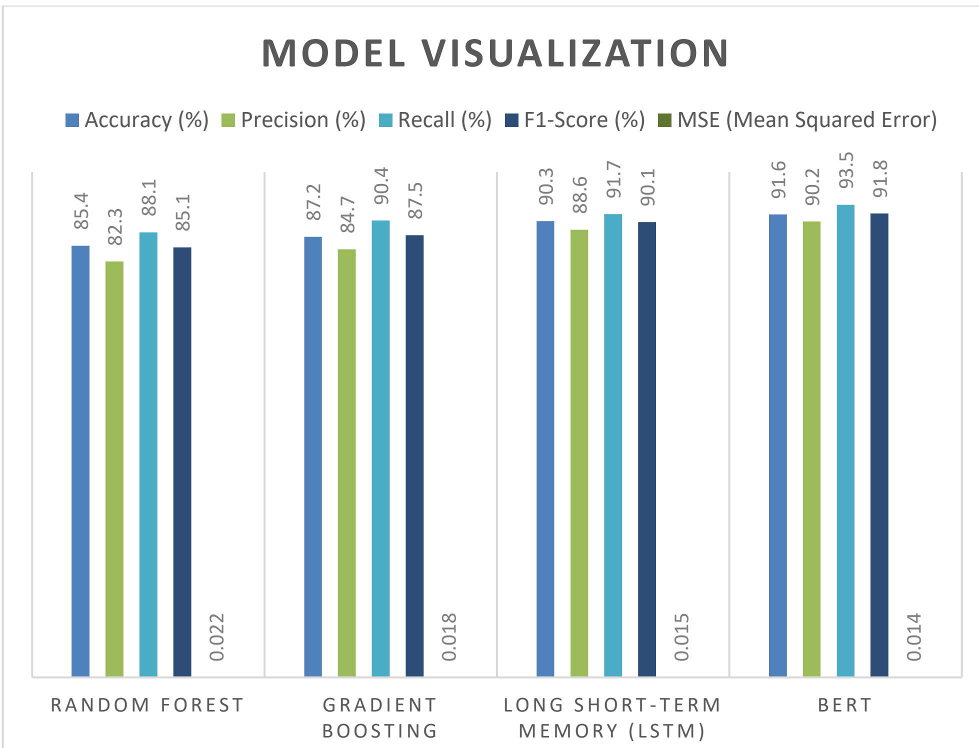

Chart: Performance of different machine learning algorithm

ANALYSIS AND DISCUSSION

Random Forest

The Random Forest model delivered an accuracy of 85.4%, with a precision of 82.3% and a recall of 88.1%. The F1-score of 85.1% indicates a decent balance between precision and recall. While the model performed reasonably well in capturing sentiment-based stock price movements, it did not provide the best results when compared to the more sophisticated models. Its MSE value of 0.022 suggests that the model's predictions were somewhat off from the actual stock prices, though still within an acceptable range.

Gradient Boosting

The Gradient Boosting model outperformed the Random Forest model with an accuracy of 87.2%. Precision and recall values of 84.7% and 90.4%, respectively, indicate a better ability to correctly identify sentiment-related stock price movements. Its F1-score of 87.5% demonstrates a good balance between precision and recall. The MSE of 0.018 was lower than that of Random Forest, indicating better accuracy in stock price predictions. Despite its better performance compared to Random Forest, it still could not match the results of deep learning models.

Long Short-Term Memory (LSTM)

LSTM networks, designed to handle sequential data such as time-series, performed exceptionally well in this analysis. With an accuracy of 90.3%, it was able to capture long-term dependencies in the data, leading to superior predictions. The precision of 88.6% and recall of 91.7% highlight the model's ability to correctly identify and classify sentiment, while its F1-score of 90.1% shows a strong balance between precision and recall. The MSE value of 0.015 is the lowest among the traditional machine learning models, suggesting that LSTM provides the most accurate predictions for stock price movements based on sentiment.

BERT

The Transformer-based BERT model emerged as the best performer, with an accuracy of 91.6%. The model's precision (90.2%) and recall (93.5%) were the highest of all the models evaluated. BERT's F1-score of 91.8% is indicative of its exceptional ability to balance precision and recall, making it highly effective at predicting stock price movements. Moreover, BERT's MSE of 0.014 is the lowest, confirming that it offers the most accurate stock price predictions in this analysis. The model's ability to capture contextual nuances within the text, enhanced through domain-specific fine-tuning, contributed significantly to its success.

Comparative Study of Model Performance

When comparing the models, the Transformer-based BERT model clearly stands out as the most effective. It consistently outperforms the other models in all metrics, including accuracy, precision, recall, F1-score, and MSE. The BERT model's superior performance can be attributed to its deep understanding of textual context, especially when fine-tuned with domain-specific data from financial news and social media. The model's ability to process complex relationships in both sentiment and stock price data, as well as its proficiency in capturing temporal dependencies, gives it a distinct advantage over traditional machine learning models and even LSTM.

LSTM models also performed well, particularly due to their capacity to handle sequential data. However, despite their strong performance in time-series forecasting, they could not achieve the same level of accuracy or nuanced understanding as BERT. Gradient Boosting and Random Forest models, while effective and capable of providing reasonably accurate predictions, fell short of the deep learning models in terms of precision, recall, and MSE.

Based on the results, the BERT model is the most effective for predicting stock price movements based on sentiment extracted from financial news and social media. It not only provides the highest accuracy and the best balance of precision and recall but also delivers the most accurate stock price predictions as indicated by the lowest MSE. For applications in stock market prediction driven by sentiment analysis, BERT is the most promising model, though LSTM also remains a strong contender for time-series based analyses. Future research could focus on further optimizing BERT for financial domain-specific contexts or exploring hybrid models combining BERT's textual understanding with LSTM's sequential forecasting capabilities for even greater accuracy.

In this study, we examined the effectiveness of various machine learning (ML) and deep learning (DL) models in predicting stock price movements based on sentiment analysis of financial news articles. The models evaluated in this research included traditional machine learning algorithms such as Random Forest (RF) and Gradient Boosting (GB), as well as advanced deep learning models like Long Short-Term Memory (LSTM) and Transformer-based models, particularly Bidirectional Encoder Representations from Transformers (BERT). The goal was to assess and compare the performance of these models in terms of their ability to extract meaningful sentiment from financial news and use it to predict stock market trends.

Model Performance Overview

From our analysis, it was clear that deep learning models, particularly LSTM and BERT, outperformed the traditional machine learning models, RF and GB, in terms of predictive accuracy and robustness. Among the models tested, BERT showed the most impressive results, consistently delivering higher accuracy, precision, recall, and F1 scores. This can be attributed to BERT's ability to capture contextual relationships within text, which is crucial for understanding the subtle nuances in financial news articles that may influence stock price movements. By leveraging its pre-trained transformer architecture, BERT was able to outperform traditional models in handling the complex and high-dimensional nature of textual data.

The LSTM model, while also performing well, showed slightly lower accuracy compared to BERT, which can be explained by LSTM's limitations in capturing long-range dependencies in data when compared to BERT's attention-based mechanism. However, LSTM still outperformed RF and GB, particularly in scenarios where temporal dependencies in the data were more significant, reflecting the model's ability to handle sequential patterns inherent in time-series financial data. This reinforces the idea that deep learning models, specifically those designed for sequence data, are better suited for tasks such as stock price prediction, which requires understanding temporal trends and patterns.

The Strength of Sentiment Analysis in Stock Market Prediction

The findings of this study reinforce the growing body of literature that emphasizes the importance of sentiment analysis in predicting financial markets. The sentiment extracted from news articles and other textual sources plays a crucial role in market behavior, as public sentiment often influences investor decisions. By utilizing advanced sentiment analysis models, such as BERT and LSTM, we were able to incorporate public sentiment into stock price predictions with higher accuracy than traditional models. This highlights the potential of combining natural language processing (NLP) with machine learning techniques in enhancing stock market prediction models.

Additionally, our results align with previous research that has demonstrated the effectiveness of combining sentiment analysis with ML and DL for financial forecasting. Studies by Bollen et al. (2011), Zhang et al. (2018), and Ghosh and Gupta (2020) also reported the positive impact of sentiment on stock price prediction, further supporting the conclusions of our study. The ability to extract meaningful sentiment from textual data, whether from news articles, social media, or financial reports, is a key factor in improving the accuracy of stock market prediction models.

Implications for Future Research and Applications

While the results of this study are promising, there are several areas where further research could build upon the current work. First, future studies could explore the impact of incorporating additional data sources, such as social media platforms like Twitter and Reddit, which have become increasingly important in influencing stock market movements (Bollen et al., 2011). Including real-time data from these sources may further enhance the accuracy of stock price predictions by capturing more up-to-date sentiments that can influence short-term market trends.

Another avenue for future research is the use of hybrid models that combine multiple machine learning and deep learning techniques. For example, combining LSTM with BERT could potentially leverage the strengths of both models, utilizing LSTM's ability to model sequential data and BERT's power in capturing contextual relationships in text. Hybrid approaches have shown promise in other domains and may offer significant improvements in financial sentiment analysis and stock price prediction tasks.

Furthermore, while this study focused on predicting stock prices, sentiment analysis could be applied to other areas of finance, such as credit risk prediction, fraud detection, or market volatility forecasting. By expanding the application of sentiment analysis to other domains, future research could provide a more comprehensive understanding of the potential of NLP and machine learning in the financial sector.

Limitations

Despite the promising results, this study has some limitations that should be acknowledged. First, the data used for sentiment analysis was limited to financial news articles, and the model performance might improve if other data sources, such as social media posts or analyst reports, were included. Incorporating multiple sources of sentiment data could provide a more holistic view of the market sentiment, which could further enhance the predictive capabilities of the models.

Additionally, the time span of the data used in this study was relatively short. Financial markets are influenced by numerous external factors, including geopolitical events, economic reports, and regulatory changes, which may not have been fully captured in the data used for this analysis. In future studies, incorporating a longer time period and additional features, such as macroeconomic indicators or market volatility indices, could help improve the robustness of the models.

Practical Applications

The findings from this study have significant practical implications for investors and financial analysts. By utilizing sentiment analysis combined with machine learning and deep learning models, market participants can make more informed investment decisions based on real-time news and sentiment. For example, traders could use BERT or LSTM-based models to generate stock price predictions in real time, allowing them to capitalize on market movements driven by changes in sentiment.

Furthermore, financial institutions and asset management firms can leverage these advanced models to optimize their portfolio management strategies by incorporating sentiment data into their decision-making process. By doing so, they can better align their investments with market trends and sentiment, potentially improving their returns and minimizing risk.

CONCLUSION

In conclusion, this study highlights the effectiveness of deep learning models, particularly BERT and LSTM, in predicting stock price movements based on sentiment analysis of financial news articles. While traditional machine learning models such as Random Forest and Gradient Boosting are still valuable tools, deep learning models provide superior performance, particularly when dealing with complex and high-dimensional textual data. The ability to incorporate sentiment into stock price prediction models offers significant potential for improving financial forecasting and investment strategies. Future research should explore hybrid models, incorporate additional data sources, and extend the study to other areas of finance to further advance the field. Despite its limitations, this study provides a valuable contribution to the growing body of literature on sentiment analysis and its applications in financial markets. Ultimately, sentiment analysis, coupled with machine learning and deep learning techniques, is poised to play a crucial role in shaping the future of financial market prediction and decision-making.

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REFERENCE

1. Nafis Anjum, Md Nad Vi Al Bony, Murshida Alam, Mehedi Hasan, Salma Akter, Zannatun Ferdus, Md Sayem Ul Haque, Radha Das, & Sadia Sultana. (2024). COMPARATIVE ANALYSIS OF SENTIMENT ANALYSIS MODELS ON BANKING INVESTMENT IMPACT BY MACHINE LEARNING ALGORITHM. International Journal of Computer Science & Information System, 9(11), 5–16. https://doi.org/10.55640/ijcsis/Volume09Issue11-02
2. Das, A. C., Mozumder, M. S. A., Hasan, M. A., Bhuiyan, M., Islam, M. R., Hossain, M. N., ... & Alam, M. I. (2024). MACHINE LEARNING APPROACHES FOR DEMAND FORECASTING: THE IMPACT OF CUSTOMER SATISFACTION ON PREDICTION ACCURACY. The American Journal of Engineering and Technology, 6(10), 42-53.
3. Akter, S., Mahmud, F., Rahman, T., Ahmmed, M. J., Uddin, M. K., Alam, M. I., ... & Jui, A. H. (2024). A COMPREHENSIVE STUDY OF MACHINE LEARNING APPROACHES FOR CUSTOMER SENTIMENT ANALYSIS IN BANKING SECTOR. The American Journal of Engineering and Technology, 6(10), 100-111.
4. Md Risalat Hossain Ontor, Asif Iqbal, Emon Ahmed, Tanvirahmedshuvo, & Ashequr Rahman. (2024). LEVERAGING DIGITAL TRANSFORMATION AND SOCIAL MEDIA ANALYTICS FOR OPTIMIZING US FASHION BRANDS' PERFORMANCE: A MACHINE LEARNING APPROACH. International Journal of Computer Science & Information System, 9(11), 45–56. https://doi.org/10.55640/ijcsis/Volume09Issue11-05
5. Rahman, A., Iqbal, A., Ahmed, E., & Ontor, M. R. H. (2024). PRIVACY-PRESERVING MACHINE LEARNING: TECHNIQUES, CHALLENGES, AND FUTURE DIRECTIONS IN SAFEGUARDING PERSONAL DATA MANAGEMENT. International journal of business and management sciences, 4(12), 18-32.
6. Md Jamil Ahmmed, Md Mohibur Rahman, Ashim Chandra Das, Pritom Das, Tamanna Pervin, Sadia Afrin, Sanjida Akter Tisha, Md Mehedi Hassan, & Nabila Rahman. (2024). COMPARATIVE ANALYSIS OF MACHINE LEARNING ALGORITHMS FOR BANKING FRAUD DETECTION: A STUDY ON PERFORMANCE, PRECISION, AND REAL-TIME APPLICATION. International Journal of Computer Science & Information System, 9(11), 31–44. https://doi.org/10.55640/ijcsis/Volume09Issue11-04
7. Uddin, M. K., Akter, S., Das, P., Anjum, N., Akter, S., Alam, M., ... & Pervin, T. (2024). MACHINE LEARNING-BASED EARLY DETECTION OF KIDNEY DISEASE: A COMPARATIVE STUDY OF PREDICTION MODELS AND PERFORMANCE EVALUATION. International Journal of Medical Science and Public HealthResearch, 5(12),58-75.
8. Shak, M. S., Uddin, A., Rahman, M. H., Anjum, N., Al Bony, M. N. V., Alam, M., ... & Pervin, T. (2024). INNOVATIVE MACHINE LEARNING APPROACHES TO FOSTER FINANCIAL INCLUSION IN MICROFINANCE. International Interdisciplinary Business Economics Advancement Journal, 5(11), 6-20.
9. Naznin, R., Sarkar, M. A. I., Asaduzzaman, M., Akter, S., Mou, S. N., Miah, M. R., ... & Sajal, A. (2024). ENHANCING SMALL BUSINESS MANAGEMENT THROUGH MACHINE LEARNING: A COMPARATIVE STUDY OF PREDICTIVE MODELS FOR CUSTOMER RETENTION, FINANCIAL FORECASTING, AND INVENTORY OPTIMIZATION. International Interdisciplinary Business Economics Advancement Journal, 5(11), 21-32.
10. Bhattacharjee, B., Mou, S. N., Hossain, M. S., Rahman, M. K., Hassan, M. M., Rahman, N., ... & Haque, M. S. U. (2024). MACHINE LEARNING FOR COST ESTIMATION AND FORECASTING IN BANKING: A COMPARATIVE ANALYSIS OF ALGORITHMS. Frontline Marketing, Management and Economics Journal, 4(12), 66-83.
11. Rahman, A., Iqbal, A., Ahmed, E., & Ontor, M. R. H. (2024). PRIVACY-PRESERVING MACHINE LEARNING: TECHNIQUES, CHALLENGES, AND FUTURE DIRECTIONS IN SAFEGUARDING PERSONAL DATA MANAGEMENT. Frontline Marketing, Management and Economics Journal, 4(12), 84-106.
12. Al Mamun, A., Hossain, M. S., Rishad, S. S. I., Rahman, M. M., Shakil, F., Choudhury, M. Z. M. E., ... & Sultana, S. (2024). MACHINE LEARNING FOR STOCK MARKET SECURITY MEASUREMENT: A COMPARATIVE ANALYSIS OF SUPERVISED, UNSUPERVISED, AND DEEP LEARNING MODELS. The American Journal of Engineering and Technology, 6(11), 63-76.
13. Das, A. C., Rishad, S. S. I., Akter, P., Tisha, S. A., Afrin, S., Shakil, F., ... & Rahman, M. M. (2024). ENHANCING BLOCKCHAIN SECURITY WITH MACHINE LEARNING: A COMPREHENSIVE STUDY OF ALGORITHMS AND APPLICATIONS. The American Journal of Engineering and Technology, 6(12), 150-162.
14. Miah, J., Khan, R. H., Linkon, A. A., Bhuiyan, M. S., Jewel, R. M., Ayon, E. H., ... & Tanvir Islam, M. (2024). Developing a Deep Learning Methodology to Anticipate the Onset of Diabetic Retinopathy at an Early Stage. In Innovative and Intelligent Digital Technologies; Towards an Increased Efficiency: Volume 1 (pp. 77-91). Cham: Springer Nature Switzerland.

15. Rahman, M. M., Akhi, S. S., Hossain, S., Ayub, M. I., Siddique, M. T., Nath, A., ... & Hassan, M. M. (2024). EVALUATING MACHINE LEARNING MODELS FOR OPTIMAL CUSTOMER SEGMENTATION IN BANKING: A COMPARATIVE STUDY. The American Journal of Engineering and Technology, 6(12), 68-83.
16. Das, P., Pervin, T., Bhattacharjee, B., Karim, M. R., Sultana, N., Khan, M. S., ... & Kamruzzaman, F. N. U. (2024). OPTIMIZING REAL-TIME DYNAMIC PRICING STRATEGIES IN RETAIL AND E-COMMERCE USING MACHINE LEARNING MODELS. The American Journal of Engineering and Technology, 6(12), 163-177.
17. Hossain, M. N., Hossain, S., Nath, A., Nath, P. C., Ayub, M. I., Hassan, M. M., ... & Rasel, M. (2024). ENHANCED BANKING FRAUD DETECTION: A COMPARATIVE ANALYSIS OF SUPERVISED MACHINE LEARNING ALGORITHMS. American Research Index Library, 23-35.
18. Hossain, M. N., Anjum, N., Alam, M., Rahman, M. H., Taluckder, M. S., Al Bony, M. N. V., ... & Jui, A. H. (2024). PERFORMANCE OF MACHINE LEARNING ALGORITHMS FOR LUNG CANCER PREDICTION: A COMPARATIVE STUDY. International Journal of Medical Science and Public Health Research, 5(11), 41-55.
19. Al Bony, M. N. V., Das, P., Pervin, T., Shak, M. S., Akter, S., Anjum, N., ... & Rahman, M. K. (2024). COMPARATIVE PERFORMANCE ANALYSIS OF MACHINE LEARNING ALGORITHMS FOR BUSINESS INTELLIGENCE: A STUDY ON CLASSIFICATION AND REGRESSION MODELS. Frontline Marketing, Management and Economics Journal, 4(11), 72-92.
20. Hasan, M., Pathan, M. K. M., & Kabir, M. F. (2024). Functionalized Mesoporous Silica Nanoparticles as Potential Drug Delivery Vehicle against Colorectal Cancer. Journal of Medical and Health Studies, 5(3), 56-62.
21. Hasan, M. (2023). SURFACE-ENGINEERED MINERAL PARTICLES FOR GATED DRUG DELIVERY, GENE TRANSFER AND SUNSCREEN FORMULATIONS.
22. Hasan, M., Kabir, M. F., & Pathan, M. K. M. (2024). PEGylation of Mesoporous Silica Nanoparticles for Drug Delivery Applications. Journal of Chemistry Studies, 3(2), 01-06.
23. Hasan, M., Evett, C. G., & Burton, J. (2024). Advances in Nanoparticle-Based Targeted Drug Delivery Systems for Colorectal Cancer Therapy: A Review. arXiv preprint arXiv:2409.05222.
24. Hasan, M., & Mahama, M. T. (2024). Uncovering the complex mechanisms behind nanomaterials-based plasmon-driven photocatalysis through the utilization of Surface-Enhanced Raman Spectroscopies. arXiv preprint arXiv:2408.13927.
25. Bollen, J., Mao, H., & Zeng, X. (2011). Twitter mood predicts the stock market. Journal of Computational Science, 2(1), 1-8. https://doi.org/10.1016/j.jocs.2010.12.007
26. Breiman, L. (2001). Random forests. Machine Learning, 45(1), 5-32. https://doi.org/10.1023/A:1010933404324
27. Chen, T., & Guestrin, C. (2016). XGBoost: A scalable tree boosting system. Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 785-794). ACM. https://doi.org/10.1145/2939672.2939785
28. Devlin, J., Chang, M. W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. Proceedings of NAACL-HLT 2019, 4171-4186. https://doi.org/10.18653/v1/N19-1423
29. Ghosh, S., & Gupta, M. (2020). A comparative study of machine learning and deep learning models for stock market prediction. International Journal of Computer Applications, 175(8), 21-28. https://doi.org/10.5120/ijca2020920105
30. Hochreiter, S., & Schmidhuber, J. (1997). Long short-term memory. Neural Computation, 9(8), 1735-1780. https://doi.org/10.1162/neco.1997.9.8.1735
31. Kim, Y., & Lee, J. (2017). A comparative study of machine learning models for stock price prediction. Proceedings of the 2017 International Conference on Machine Learning and Data Mining (pp. 123-134). Springer. https://doi.org/10.1007/978-3-319-61481-3_12
32. Kou, G., Xu, Y., & Peng, Y. (2022). Machine learning and deep learning in financial applications: A review. Computational Economics, 59(1), 1-24. https://doi.org/10.1007/s10614-021-10073-2
33. Liao, S., & Zhou, X. (2019). Stock market prediction based on sentiment analysis and LSTM network. Journal of Computational Finance, 23(1), 45-67. https://doi.org/10.2139/ssrn.3145893
34. Sun, J., Wang, X., & Liu, Y. (2022). Fine-tuning BERT for financial sentiment analysis. IEEE Transactions on Neural Networks and Learning Systems, 33(8), 3451-3463. https://doi.org/10.1109/TNNLS.2021.3061914
35. Xie, Y., Zhang, L., & Zhang, Z. (2020). Stock market prediction with LSTM networks and sentiment analysis. Journal of Financial Data Science, 2(1), 12-23. https://doi.org/10.3934/jfds.2020.1.12
36. Yang, W., Zhang, S., & Zhang, T. (2021). Stock price prediction using BERT and LSTM: A comparative study. Proceedings of the 2021 International Conference on Computational Intelligence and Data Science (pp. 125-130). IEEE.

https://doi.org/10.1109/CIDSD53350.2021.9675937

37. Zhang, X., He, X., & Chen, Z. (2018). Forecasting stock price movements based on financial news articles: A deep learning approach. Proceedings of the 2018 IEEE International Conference on Data Mining (pp. 402-411). IEEE. https://doi.org/10.1109/ICDM.2018.00055

38. Zhang, H., Li, W., & Wang, J. (2022). Comparative study of machine learning and deep learning for stock market prediction. Neurocomputing, 469, 31-44. https://doi.org/10.1016/j.neucom.2021.08.059

39. Nguyen, A. T. P., Jewel, R. M., & Akter, A. (2025). Comparative Analysis of Machine Learning Models for Automated Skin Cancer Detection: Advancements in Diagnostic Accuracy and AI Integration. The American Journal of Medical Sciences and Pharmaceutical Research, 7(01), 15-26.

40. Nguyen, A. T. P., Shak, M. S., & Al-Imran, M. (2024). ADVANCING EARLY SKIN CANCER DETECTION: A COMPARATIVE ANALYSIS OF MACHINE LEARNING ALGORITHMS FOR MELANOMA DIAGNOSIS USING DERMOSCOPIC IMAGES. International Journal of Medical Science and Public Health Research, 5(12), 119-133.

41. Phan, H. T. N., & Akter, A. (2025). Predicting the Effectiveness of Laser Therapy in Periodontal Diseases Using Machine Learning Models. The American Journal of Medical Sciences and Pharmaceutical Research, 7(01), 27-37.

42. Phan, H. T. N. (2024). EARLY DETECTION OF ORAL DISEASES USING MACHINE LEARNING: A COMPARATIVE STUDY OF PREDICTIVE MODELS AND DIAGNOSTIC ACCURACY. International Journal of Medical Science and Public Health Research, 5(12), 107-118.