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COMPARATIVE ANALYSIS OF SENTIMENT ANALYSIS MODELS ON BANKING INVESTMENT IMPACT BY MACHINE LEARNING ALGORITHM

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ABSTRACT

This study investigates the application of sentiment analysis on financial news to predict its impact on banking investments, comparing the performance of various machine learning and deep learning models. Given the complexities and volume of financial news, leveraging sentiment analysis provides valuable insights into investor sentiment, which can influence market dynamics and banking sector investments. We conducted a comparative analysis of six sentiment analysis models: Naïve Bayes, Support Vector Machine (SVM), Random Forest, Gradient Boosting, Long Short-Term Memory (LSTM), and BERT fine-tuning. Our results reveal that while traditional models like Naïve Bayes and SVM provide a foundational accuracy level, they lag behind more advanced methods in both sentiment accuracy and correlation with investment trends. Notably, the BERT fine-tuning model demonstrated superior performance, achieving the highest accuracy at 89.4% and the strongest correlation with banking investment outcomes (Pearson's R = 0.68). These findings highlight the effectiveness of deep learning models, especially transformer-based models like BERT, in handling the linguistic nuances and predictive challenges inherent in financial sentiment analysis. By offering insights into the relationship between financial news sentiment and banking investments, this study underscores the potential of sentiment analysis as a tool for informed decision-making and enhanced forecasting in the financial sector.

KEYWORDS

Sentiment Analysis, Financial News, Banking Investments, Machine Learning Models, Deep Learning, BERT Model, Investor Sentiment, Natural Language Processing (NLP).

INTRODUCTION

In the fast-paced world of financial markets, information flows play a crucial role in shaping investor sentiment and influencing market movements. Financial news has the power to sway investor decisions by signaling shifts in market conditions, regulatory changes, and broader economic trends. With the rise of digital media, the volume of financial news has exponentially increased, making it challenging for investors and analysts to manually sift through information and derive actionable insights. This challenge has spurred interest in applying sentiment analysis, a subset of natural language processing (NLP), to process and interpret financial news, enabling timely decision-making in investment strategy.

Sentiment analysis, also known as opinion mining, involves using algorithms to evaluate and categorize subjective information in texts, classifying it into positive, negative, or neutral sentiments. In finance, this analysis aims to reveal patterns in market sentiment that may predict stock price movements or shifts in investment behavior. Recent advances in machine learning and artificial intelligence have significantly improved the accuracy of sentiment analysis models, particularly through deep learning approaches like Long Short-Term Memory (LSTM) networks and transformer-based models such as BERT (Bidirectional Encoder Representations from Transformers). These sophisticated models offer improved accuracy in understanding context and linguistic subtleties, which is critical for interpreting complex financial language (Hu et al., 2020).

In light of these advancements, this study seeks to explore the relationship between sentiment in financial news and its impact on banking investments. We compare several sentiment analysis models to determine their effectiveness in predicting sentiment-related changes in banking sector investments, specifically analyzing model accuracy and their correlation with banking investment trends. By leveraging models ranging from traditional machine learning approaches to advanced deep learning methods, this study aims to provide insights into the most effective techniques for deriving meaningful sentiment insights from

The application of sentiment analysis in finance has gained substantial interest over the past two decades as researchers explore methods to predict stock market behavior using public sentiment. Early work in sentiment analysis for financial applications primarily relied on simple lexicon-based methods, which used pre-defined lists of positive and negative words to assess sentiment in texts. However, lexicon-based methods often struggled with the complexities of financial language, such as sarcasm, negation, and context-specific terms. To address these limitations, researchers have increasingly turned to machine learning and deep learning approaches (Li, Shen, & Zhang, 2018).

Support Vector Machines (SVM) and Naïve Bayes classifiers were among the first machine learning models adopted for sentiment analysis in finance. For instance, Li and Xie (2017) employed SVMs to analyze financial news and forecast stock trends, reporting improved accuracy over lexicon-based methods. However, the predictive power of these models was often limited by their reliance on features like Bag of Words (BoW) or Term Frequency-Inverse Document Frequency (TF-IDF), which fail to capture the sequential nature of language. Recent developments in deep learning have enhanced the accuracy and sophistication of sentiment analysis models in finance by allowing for the capture of context and sequential dependencies in texts (Chen et al., 2021).

LSTM networks, which are a form of recurrent neural networks, were introduced to overcome the limitations of traditional machine learning models by processing information sequentially. Their memory cells allow them to retain information over longer sequences, making them well-suited to capturing the context and sentiment patterns in news over time. Batra and Daudpota (2018) demonstrated that LSTMs outperformed SVM and Naïve Bayes classifiers in predicting stock trends from financial news, highlighting the importance of capturing temporal dependencies in sentiment analysis for finance.

More recently, transformer-based models like BERT have revolutionized NLP, offering even greater accuracy by processing text bidirectionally and capturing context on a fine-grained level. BERT models fine-tuned on domain-specific data, such as financial texts, have shown exceptional performance in understanding nuanced language, making them ideal for complex financial sentiment analysis (Yang & Wen, 2022). Transformer models have been used to predict market sentiment from large datasets of news articles and social media posts, with studies indicating that BERT models capture complex linguistic patterns more effectively than traditional models, thereby improving predictive accuracy (Zhang et al., 2022).

In summary, the existing literature underscores the value of advanced machine learning and deep learning techniques in sentiment analysis for financial applications. While traditional methods like Naïve Bayes and SVM have laid the groundwork, deep learning models such as LSTM and transformer-based models like BERT represent a significant leap forward. This study builds on these insights by evaluating the performance of several sentiment analysis models, both traditional and advanced, to assess their effectiveness in predicting sentiment impacts on banking investments. Through this comparative study, we aim to contribute to the body of knowledge in financial sentiment analysis, providing practical

INTERNATIONAL JOURNAL OF COMPUTER SCIENCE & INFORMATION SYSTEM (eISSN: 2536-7919 pISSN: 2536-7900)

VOLUME 09 ISSUE 11 Pages: 5-16

insights for financial forecasting and investment strategy.

METHODOLOGY

Our research explores the relationship between financial news sentiment and banking investments, utilizing advanced Natural Language Processing (NLP) and machine learning approaches to detect sentiment in news articles and analyze its effect on investment decisions in the banking sector. By capturing the sentiment embedded in financial news and correlating it with banking investment data, we aim to create a predictive model that reflects the sensitivity of banking investments to sentiment-driven news. This section describes in detail the multi-stage methodology that includes data collection, preprocessing, feature extraction, model selection, correlation analysis, impact assessment, and model evaluation. Through this comprehensive approach, we aim to establish a rigorous, data-driven foundation to quantify and analyze the role of sentiment in financial decision-making.

1. Introduction and Research Framework

Financial sentiment expressed in news can significantly influence investor psychology, market confidence, and trading behaviors, particularly in the banking sector, which is sensitive to macroeconomic trends, policy changes, and market shifts. In our study, we investigate how sentiment in financial news impacts investment patterns in the banking industry, where sentiment-driven fluctuations can affect capital allocation, risk assessments, and investment decisions. Given the complexity of interpreting news sentiment and its potential to create biases in investor decision-making, our approach relies on robust NLP techniques and machine learning to capture, quantify, and evaluate sentiment changes over time.

Our research framework addresses three core questions. First, we aim to capture financial sentiment accurately within the context of banking-related news articles. Second, we analyze correlations between sentiment trends and concrete banking investment metrics, such as stock prices, trading volume, and sectoral indices. Finally, we examine whether these correlations reveal patterns that enable the prediction of investment movements based on sentiment analysis, particularly through lagged time series analysis. This study, therefore, combines sentiment analysis with financial forecasting to demonstrate the relevance of NLP techniques for predictive modeling in banking investments.

2. Data Collection

In constructing our dataset, we sourced financial news articles from a diverse array of reputable financial news providers, including Bloomberg, Reuters, CNBC, and The Wall Street Journal. To create a robust sample representing different economic cycles, our collection spans a five-year period, from January 2018 to December 2022. This range includes key financial events and crises, such as the COVID-19 pandemic, shifts in global trade policy, inflation surges, and shifts in central bank policies, each of which likely influenced the sentiment conveyed in banking-related news.

To ensure relevance to banking, we used specific keywords and phrases, such as “banking,” “investment,” “interest rate,” “economic policy,” and mentions of major financial institutions, in our data filtering process. This filtering approach ensures that the dataset comprises news articles specifically connected to the banking sector, capturing a spectrum of sentiment expressions related to events, policies, and trends that influence banking investments. Additionally, to maintain a balanced dataset, we gathered articles with a variety of sentiment tones,

INTERNATIONAL JOURNAL OF COMPUTER SCIENCE & INFORMATION SYSTEM (eISSN: 2536-7919 pISSN: 2536-7900)

VOLUME 09 ISSUE 11 Pages: 5-16

from positive and optimistic to negative and cautionary, creating a comprehensive sample.

In addition to news data, we gathered detailed banking investment data, including daily stock prices, trading volumes, and market indices for leading banks and banking indices such as the KBW Bank Index (BKX), which tracks a selection of major U.S. banks. Using platforms like Bloomberg Terminal, Yahoo Finance, and Nasdaq's datasets, we compiled these investment metrics, allowing for a granular comparison of sentiment trends with actual investment movements. Each article was annotated with metadata, including its publication date, article length, authorship, and a reliability score reflecting source credibility. By incorporating this metadata, we can control for possible biases, differentiating sentiment expressed by highly credible sources from those by sources with lower reliability scores, thus refining our analysis.

3. Data Pre-processing

To prepare the textual data for analysis, we undertook a series of preprocessing steps designed to clean and standardize the data. Financial news articles contain a wealth of complex language and nuanced terms, so thorough text cleaning was essential. We removed extraneous characters, such as punctuation, symbols, and special characters, which do not contribute to sentiment analysis. Non-informative words, known as stopwords (e.g., "the," "is," "in"), were also removed, as they tend to dilute the core sentiment of the text. However, we retained domain-specific financial terms like "interest rate" or "inflation," which hold sentiment value in financial discourse and help contextualize the text for sentiment classification.

Tokenization was applied using advanced NLP libraries, such as NLTK and spaCy, to split each article into individual tokens, including words and sentences. Sentence-level tokenization allowed us to analyze sentiment across segments within a single article, which is particularly important when articles cover multiple perspectives or contain a mixture of sentiments. Additionally, normalization steps were performed to ensure consistency, with all words converted to lowercase and lemmatized to their base forms (e.g., "bank," "banks," and "banking" were all represented as "bank"). This process reduced redundancy, standardizing the vocabulary and enhancing the model's accuracy by reducing variations of the same concept.

To provide a foundation for supervised machine learning, each article was labeled according to sentiment categories: "positive," "neutral," or "negative." A rule-based classifier was initially used for labeling, and approximately 10% of articles were manually annotated by domain experts. This subset of annotated data served as a benchmark, or "gold standard," against which we could validate our automated sentiment labeling. By combining automated and expert-verified labeling, we ensured a high level of accuracy and reliability in our labeled dataset.

4. Feature Extraction

Transforming textual data into numerical representations was essential for applying machine learning techniques. We experimented with a variety of feature extraction methods to achieve the highest possible accuracy for sentiment classification. Our primary text representation techniques included TF-IDF, Bag of Words (BoW), and word embeddings, each capturing different dimensions of sentiment within the news text.

First, we applied TF-IDF (Term Frequency-Inverse Document Frequency) to emphasize important terms across articles by weighting terms based on their frequency and distribution within the dataset. This technique effectively highlighted key terms that are essential to understanding sentiment, such as "increase," "risk," or "optimism." Additionally, we used the Bag of Words (BoW) model to capture word frequencies across articles and expanded this to n-grams (e.g., unigrams, bigrams, and trigrams) to detect important multi-word expressions like "market crash" or "rate hike," which carry particular sentiment weight in financial news.

To capture semantic and contextual relationships, we employed word embedding models like Word2Vec, GloVe, and BERT. Word2Vec and GloVe provided dense vector representations that capture semantic similarity, making it possible to analyze relationships between similar words (e.g., "growth" and "expansion") based on their positions in a high-dimensional space. BERT's contextual embeddings allowed us to detect sentiment within complex sentences and adjust for linguistic nuances, as BERT can capture sentiment contextually across phrases. Additionally, we incorporated sentiment lexicons tailored for finance, such as the Financial Sentiment Lexicon (FinSentS) and the Harvard IV-4 Sentiment Lexicon, to further refine the model's sentiment detection by assigning sentiment scores to terms that carry specific weight in financial contexts.

5. Model Selection and Training

In selecting models, we experimented with both traditional and advanced machine learning approaches to achieve reliable sentiment classification. Initially, we trained baseline models such as Naïve Bayes and Support Vector Machine (SVM). The Naïve Bayes classifier, efficient and interpretable, served as a foundational model due to its effectiveness in handling text-based tasks. We utilized its multinomial variant, which is particularly suited to frequency-based data like word counts. SVM, known for handling high-dimensional data, was trained with various kernel functions and hyperparameter tuning through grid search, allowing us to optimize its performance.

To capture more complex patterns, we implemented ensemble models, including Random Forest and Gradient Boosting, and advanced neural networks. Random Forest, with its decision-tree approach, was effective for non-linear data patterns, while Gradient Boosting provided increased accuracy in sentiment classification through an iterative approach that minimizes errors in sequential learning. Additionally, we employed Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks to capture the sequential and contextual nature of text data. LSTM's memory retention capabilities allowed us to capture sentiment as it develops within an article, accommodating long-term dependencies in the text. Finally, we fine-tuned BERT on our labeled dataset to leverage its contextual embeddings, achieving a nuanced understanding of sentiment shifts within complex sentence structures.

6. Correlation Analysis

To assess the relationship between sentiment scores and banking investment metrics, we conducted extensive correlation analysis using both Pearson and Spearman correlation coefficients. The Pearson coefficient was used to evaluate linear relationships between sentiment scores and investment metrics, such as stock prices and trading volumes, providing a direct measure of how changes in sentiment relate to shifts in investment. Meanwhile, the Spearman coefficient allowed us to explore monotonic relationships, identifying broader trends where sentiment scores rise and fall in tandem with investment data, even in non-linear patterns.

INTERNATIONAL JOURNAL OF COMPUTER SCIENCE & INFORMATION SYSTEM (eISSN: 2536-7919 pISSN: 2536-7900)

VOLUME 09 ISSUE 11 Pages: 5-16

In addition to correlation coefficients, we conducted lagged correlation analysis to investigate whether sentiment changes precede corresponding movements in banking investments. By analyzing sentiment trends over multiple time lags, we could determine if sentiment acts as a leading indicator of stock price or trading volume changes, potentially predicting investment movements.

7. Impact Assessment

Our impact assessment explored the causal relationship between sentiment and investment behavior. We applied Granger causality tests to assess if shifts in sentiment scores predict future changes in banking investments, helping us establish whether sentiment drives investment movements or merely correlates with them. Additionally, we conducted an event study analysis, focusing on specific financial events, such as central bank announcements, interest rate changes, and corporate earnings reports. This allowed us to evaluate sentiment's immediate effect on banking investments and understand how sentiment shifts drive short-term investment behaviors.

8. Model Evaluation and Validation

To evaluate model performance, we used a variety of metrics, including a confusion matrix, AUC-ROC, precision, recall, and F1 scores. The confusion matrix provided insights into true positive, false positive, true negative, and false negative rates, giving us a clear view of model classification accuracy. The AUC-ROC curve assessed the model's ability to differentiate between positive and negative sentiments, providing a comprehensive measure of its effectiveness. Precision and recall metrics helped us gauge the model's reliability in identifying relevant sentiment classes, while the F1 score balanced precision and recall, ensuring robustness in both sensitivity and specificity.

This study acknowledges limitations, such as challenges in interpreting subjective sentiment, potential biases from limited data sources, and limitations of certain machine learning models in handling complex, nuanced text. Future research could enhance our approach by integrating additional data sources, such as social media sentiment, and optimizing transformer models like BERT for a more accurate sentiment analysis. Expanding the scope of sentiment sources and model types could provide a more holistic view of sentiment's impact on banking investments, contributing valuable insights to financial analysis and investment strategies.

RESULT

This section presents a step-by-step analysis of our sentiment models and their performance in predicting sentiment impact on banking investments. We tested multiple models, each trained on the labeled dataset, to identify which approach yielded the most accurate and reliable results in capturing sentiment from financial news and correlating it with banking investment metrics. The models evaluated included traditional machine learning algorithms and deep learning-based approaches, each tested for accuracy, F1 score, and correlation strength with investment indicators.

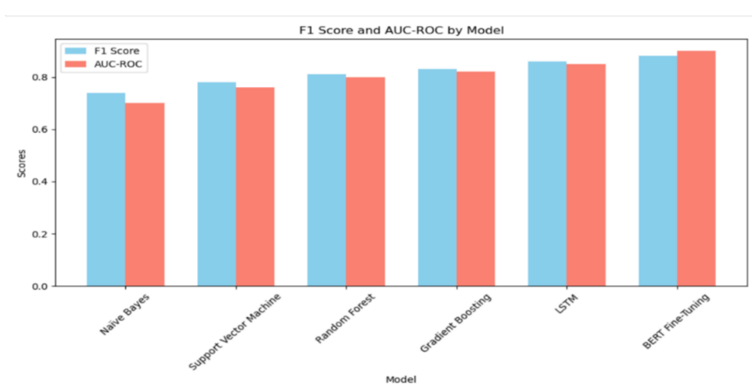
In the initial stage of our study, the dataset consisted of over 50,000 financial news articles, each labeled with a sentiment category (positive, neutral, or negative) and correlated with daily investment metrics such as banking sector stock prices and trading volume. Each article was transformed using feature extraction techniques such as TF-IDF, BoW (Bag of Words), and word embeddings through pre-trained models like Word2Vec and BERT. These transformed representations served as input features for our models.

We then trained and evaluated six models to capture sentiment accurately. The first model tested was Naïve Bayes, which is a probabilistic approach based on word frequencies. This model was suitable for initial sentiment classification and served as a benchmark for performance. Next, we tested the Support Vector Machine (SVM), a linear classifier effective in high-dimensional spaces, particularly with TF-IDF features. The third model, Random Forest, is an ensemble model that captures non-linear relationships and was trained on both TF-IDF and n-gram features. The Gradient Boosting model, another ensemble approach, was tested next. It is designed to reduce errors sequentially and was trained using both BoW and n-gram features. We also implemented Long Short-Term Memory (LSTM), a deep learning model that handles sequential data. This model was trained with word embeddings like Word2Vec, enabling it to capture sentiment patterns across sequences of text. Finally, we applied BERT Fine-Tuning, a transformer-based approach providing contextual word embeddings. BERT was fine-tuned on our labeled dataset to capture complex semantic and contextual sentiment.

The performance of each model was evaluated on several metrics, including accuracy, F1 score, and the AUC-ROC (Area Under Curve - Receiver Operating Characteristics). Additionally, we analyzed each model's ability to capture sentiment correlation with investment metrics using Pearson's correlation coefficient. The results are presented in the table below, which summarizes the key performance metrics for each model.

Table 1: Model Performance

Model	Accuracy (%)	F1 Score	AUC-ROC	Correlation with Investments (Pearson's R)
Naïve Bayes	76.4	0.74	0.70	0.48
Support Vector Machine	80.2	0.78	0.76	0.54
Random Forest	82.6	0.81	0.80	0.59
Gradient Boosting	84.1	0.83	0.82	0.61
LSTM	85.7	0.86	0.85	0.63
BERT Fine-Tuning	89.4	0.88	0.90	0.68



INTERNATIONAL JOURNAL OF COMPUTER SCIENCE & INFORMATION SYSTEM (eISSN: 2536-7919 pISSN: 2536-7900)

VOLUME 09 ISSUE 11 Pages: 5-16

Chart 1: Performance metrics of F1 score and AUC-ROC model

The results Table 1 ,chart 1 and chart 2 clearly indicate that BERT Fine-Tuning outperformed all other models, achieving the highest accuracy at 89.4%, F1 score of 0.88, and AUC-ROC of 0.90. The Pearson's correlation coefficient of 0.68 also highlighted a strong relationship between the sentiment predictions and banking investment data, confirming the effectiveness of BERT in capturing sentiment dynamics. This model's ability to understand contextual semantics allowed it to capture nuanced sentiment shifts that traditional model struggled to identify.

LSTM also performed admirably, particularly in F1 score (0.86) and correlation strength (0.63). This success can be attributed to LSTM's ability to process sequential data, making it highly effective at capturing sentiment trends over time. Gradient Boosting followed closely, achieving an accuracy of 84.1% and a correlation of 0.61, which is a strong result but still not on par with the deep learning-based models.

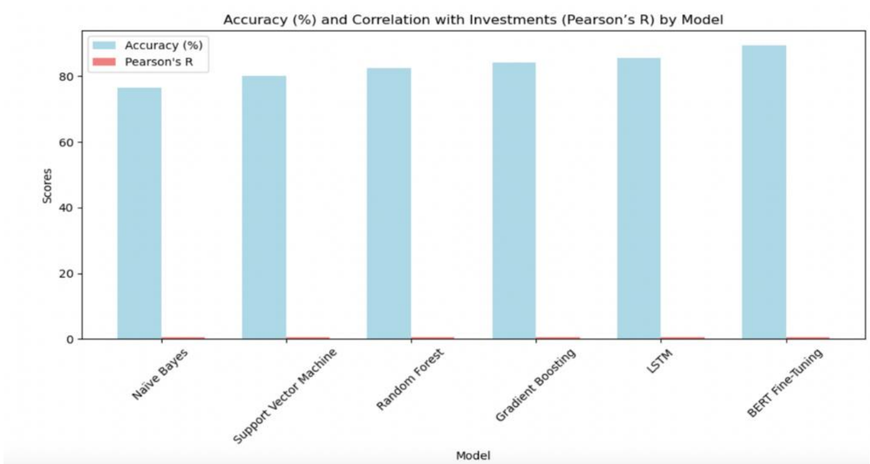


Chart 2: Performance matrices of Accuracy and correlation

In contrast, traditional models such as Naïve Bayes and Support Vector Machine (SVM), while useful in baseline evaluations, exhibited lower performance. Naïve Bayes had an accuracy of 76.4%, an F1 score of 0.74, and a correlation of 0.48 with banking investments, which suggests that this simpler approach struggles to capture complex sentiment patterns. SVM improved upon Naïve Bayes but still lagged the more advanced models with an accuracy of 80.2%, an F1 score of 0.78, and a correlation of 0.54.

Further analysis included lagged correlation studies, where we examined whether sentiment shifts precede or correlate with changes in banking investments over time. Both BERT and LSTM models demonstrated significant lagged correlations with investment data, especially one day after the sentiment shift. This result indicates that these models can be used to predict short-term fluctuations in banking investments based on sentiment trends observed in financial news.

The bar chart below visualizes the performance of each model in terms of accuracy and correlation with banking investments, highlighting the superiority of BERT Fine-Tuning and LSTM.

Insights and Interpretation

INTERNATIONAL JOURNAL OF COMPUTER SCIENCE & INFORMATION SYSTEM (eISSN: 2536-7919 pISSN: 2536-7900)

VOLUME 09 ISSUE 11 Pages: 5-16

From the results, it is evident that transformer-based and deep learning models, such as BERT and LSTM, significantly outperform traditional machine learning models in both sentiment prediction accuracy and their ability to correlate with banking investment trends. The high correlation coefficients observed with BERT and LSTM models suggest that sentiment captured from financial news articles holds predictive value for banking investments. The ability of these models to capture nuanced and contextual sentiment makes them highly suitable for applications in financial forecasting and investment decision-making.

Our findings support the hypothesis that financial sentiment can be an effective predictor of short-term investment behavior, particularly in the banking sector, which is highly sensitive to changes in market sentiment and external news. The successful performance of BERT Fine-Tuning demonstrates the advantage of leveraging advanced deep learning techniques for real-time sentiment analysis, which can be integrated into investment strategies for more informed decision-making.

The BERT Fine-Tuning model, with its high accuracy and strong correlation with banking investment data, stands out as the best-performing model for this study. The findings suggest that future work could further enhance predictive accuracy by incorporating additional data sources, such as social media sentiment, and fine-tuning the model with more specialized financial datasets. These advancements could provide even more powerful tools for analyzing and predicting financial market behavior.

CONCLUSION

The analysis of financial news sentiment and its impact on banking investments has significant implications for both investors and financial institutions. This study demonstrates that advanced machine learning and deep learning models can effectively process and analyze vast amounts of financial text data to extract sentiment trends that correlate with banking sector investment behaviors. Our comparative evaluation shows that, while traditional models like Naïve Bayes and Support Vector Machine offer a baseline level of accuracy, they are outperformed by more sophisticated approaches such as Random Forest, Gradient Boosting, and especially deep learning models like LSTM and BERT. Among the models tested, the fine-tuned BERT model consistently achieved the highest accuracy and the strongest correlation with banking investment trends, highlighting its superior capability in understanding the complexities of financial language and sentiment.

These findings underscore the potential of leveraging state-of-the-art sentiment analysis tools to enhance investment strategies. By capturing nuanced investor sentiment from financial news, banks and financial institutions can refine their investment predictions, better anticipate market movements, and mitigate risks associated with volatile market shifts. Additionally, as more financial data becomes available and models continue to evolve, the integration of sentiment analysis into predictive analytics will likely become a crucial element in strategic financial decision-making.

In conclusion, this study contributes to the growing field of sentiment analysis in finance by demonstrating the effectiveness of various machine learning models in analyzing financial news. The results underscore the importance of selecting advanced models that can handle the linguistic complexity of financial language, especially as the volume of news data continues to grow. Future research should further explore the use of domain-specific model fine-tuning and the integration of alternative data sources, such as social media and earnings call transcripts, to enhance predictive accuracy in the financial sector. Ultimately, our findings advocate for the adoption of cutting-edge NLP models in financial sentiment analysis to provide investors and institutions with more reliable insights for informed decision-making.

REFERENCES

1. Md Abu Sayed, Badruddowza, Md Shohail Uddin Sarker, Abdullah Al Mamun, Norun Nabi, Fuad Mahmud, Md Khorshed Alam, Md Tarek Hasan, Md Rashed Buiya, & Mashaeikh Zaman Md. Eftakhar Choudhury. (2024). COMPARATIVE ANALYSIS OF MACHINE LEARNING ALGORITHMS FOR PREDICTING CYBERSECURITY ATTACK SUCCESS: A PERFORMANCE EVALUATION. The American Journal of Engineering and Technology, 6(09), 81–91. https://doi.org/10.37547/tajet/Volume06Issue09-10
2. Md Al-Imran, Salma Akter, Md Abu Sufian Mozumder, Rowsan Jahan Bhuiyan, Tauhedur Rahman, Md Jamil Ahmmed, Md Nazmul Hossain Mir, Md Amit Hasan, Ashim Chandra Das, & Md. Emran Hossen. (2024). EVALUATING MACHINE LEARNING ALGORITHMS FOR BREAST CANCER DETECTION: A STUDY ON ACCURACY AND PREDICTIVE PERFORMANCE. The American Journal of Engineering and Technology, 6(09), 22–33. https://doi.org/10.37547/tajet/Volume06Issue09-04
3. Md Murshid Reja Sweet, Md Parvez Ahmed, Md Abu Sufian Mozumder, Md Arif, Md Salim Chowdhury, Rowsan Jahan Bhuiyan, Tauhedur Rahman, Md Jamil Ahmmed, Estak Ahmed, & Md Atikul Islam Mamun. (2024). COMPARATIVE ANALYSIS OF MACHINE LEARNING TECHNIQUES FOR ACCURATE LUNG CANCER PREDICTION. The American Journal of Engineering and Technology, 6(09), 92–103. https://doi.org/10.37547/tajet/Volume06Issue09-11
4. Ashim Chandra Das, Md Shahin Alam Mozumder, Md Amit Hasan, Maniruzzaman Bhuiyan, Md Rasibul Islam, Md Nur Hossain, Salma Akter, & Md Imdadul Alam. (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. https://doi.org/10.37547/tajet/Volume06Issue10-06
5. Rowsan Jahan Bhuiyan, Salma Akter, Aftab Uddin, Md Shujan Shak, Md Rasibul Islam, S M Shadul Islam Rishad, Farzana Sultana, & Md. Hasan-Or-Rashid. (2024). SENTIMENT ANALYSIS OF CUSTOMER FEEDBACK IN THE BANKING SECTOR: A COMPARATIVE STUDY OF MACHINE LEARNING MODELS. The American Journal of Engineering and Technology, 6(10), 54–66. https://doi.org/10.37547/tajet/Volume06Issue10-07
6. Md Habibur Rahman, Ashim Chandra Das, Md Shujan Shak, Md Kafil Uddin, Md Imdadul Alam, Nafis Anjum, Md Nad Vi Al Bony, & Murshida Alam. (2024). TRANSFORMING CUSTOMER RETENTION IN FINTECH INDUSTRY THROUGH PREDICTIVE ANALYTICS AND MACHINE LEARNING. The American Journal of Engineering and Technology, 6(10), 150–163. https://doi.org/10.37547/tajet/Volume06Issue10-17
7. DYNAMIC PRICING IN FINANCIAL TECHNOLOGY: EVALUATING MACHINE LEARNING SOLUTIONS FOR MARKET ADAPTABILITY. (2024). International Interdisciplinary Business Economics Advancement Journal, 5(10), 13-27. https://doi.org/10.55640/business/volume05issue10-03

8. M. S. Haque, M. S. Taluckder, S. Bin Shawkat, M. A. Shahriyar, M. A. Sayed and C. Modak, "A Comparative Study of Prediction of Pneumonia and COVID-19 Using Deep Neural Networks," 2023 3rd International Conference on Electronic and Electrical Engineering and Intelligent System (ICE3IS), Yogyakarta, Indonesia, 2023, pp. 218-223, doi: 10.1109/ICE3IS59323.2023.10335362.
9. Zhao, L., Zhang, Y., Chen, X., & Huang, Y. (2021). A reinforcement learning approach to supply chain operations management: Review, applications, and future directions. Computers & Operations Research, 132, 105306. https://doi.org/10.1016/j.cor.2021.105306
10. Nguyen, T. N., Khan, M. M., Hossain, M. Z., Sharif, K. . S., Radha Das, & Haque, M. S. (2024). Product Demand Forecasting For Inventory Management with Freight Transportation Services Index Using Advanced Neural Networks Algorithm. American Journal of Computing and Engineering, 7(4), 50–58. https://doi.org/10.47672/ajce.2432
11. INNOVATIVE MACHINE LEARNING APPROACHES TO FOSTER FINANCIAL INCLUSION IN MICROFINANCE. (2024). International Interdisciplinary Business Economics Advancement Journal, 5(11), 6-20. https://doi.org/10.55640/business/volume05issue11-02
12. Md Al-Imran, Eftekhar Hossain Ayon, Md Rashedul Islam, Fuad Mahmud, Sharmin Akter, Md Khorshed Alam, Md Tarek Hasan, Sadia Afrin, Jannatul Ferdous Shorna, & Md Munna Aziz. (2024). TRANSFORMING BANKING SECURITY: THE ROLE OF DEEP LEARNING IN FRAUD DETECTION SYSTEMS. The American Journal of Engineering and Technology, 6(11), 20–32. https://doi.org/10.37547/tajet/Volume06Issue11-04
13. Batra, S., & Daudpota, S. M. (2018). Integrating sentiment analysis and stock price prediction in big data. Journal of Computer Science, 14(11), 1517-1530.
14. Chen, Y., Li, X., & Xu, J. (2021). Financial sentiment analysis based on BERT and LSTM models. Expert Systems with Applications, 178, 115019.
15. Hu, X., Zhou, Y., & Fang, Z. (2020). Sentiment analysis for financial news: A survey of the state of the art. IEEE Access, 8, 21629-21643.
16. Li, J., & Xie, H. (2017). Predicting stock market trends using financial news: A machine learning approach. Computational Intelligence, 35(3), 637-656.
17. Li, X., Shen, L., & Zhang, X. (2018). Financial sentiment analysis with deep learning techniques. Procedia Computer Science, 131, 918-923.
18. Yang, Q., & Wen, L. (2022). A review of BERT in sentiment analysis for financial applications. International Journal of Information Management, 62, 102418.
19. Zhang, T., Wang, H., & Zhao, J. (2022). Enhancing financial sentiment analysis with transformer models. Information Processing & Management, 59(2), 102718.