HENDESE TEKNİK BİLİMLER ve MÜHENDİSLİK DERGİSİ
JOURNAL of HENDESE TECHNICAL SCIENCES and ENGINEERING
RESEARCH ARTICLE

Combining Sentiment Analysis Models Using Stacking Ensemble Learning Techniques on BIST30 Stocks

Mahmut Sami SIVRI[*1]

[*1]*Faculty of Engineering, Istanbul Technical University, Istanbul, TÜRKİYE*

(**Received:** 06.08.2024, **Accepted:** 22.10.2024, **Published Online:** 27.10.2024)

Keywords
Sentiment Analysis,
Stock Prediction,
Machine Learning,
Stacking

ABSTRACT

In recent years, sentiment analysis has become a crucial task in the field of natural language processing (NLP). Despite significant advancements in individual sentiment analysis models, combining multiple models can further enhance performance and robustness. This paper proposes an ensemble model using stacking to integrate the outputs of different sentiment analysis models applied to news articles related to BIST30 stocks traded on Borsa Istanbul. The base models include Long Short-Term Memory (LSTM), Bidirectional Encoder Representations from Transformers (BERT), Naive Bayes, and Support Vector Machines (SVM). The meta-learner is a logistic regression model that aggregates the predictions of the base models. This ensemble approach demonstrates improved accuracy and generalization capabilities over single-model approaches in analyzing the sentiment of financial news.

Corresponding Author: sivri@itu.edu.tr
Volume: 1 **Issue:** 2

Cite as: Sivri, M.S., “Combining Sentiment Analysis Models Using Stacking Ensemble Learning Techniques on BIST30 Stocks”, Hendese, Vol. 1, Issue 2, Pages 91-97, 2024.

Doi: 10.5281/zenodo.13996517

1. INTRODUCTION

Sentiment analysis**,** a subfield of natural language processing (NLP)**,** aims to identify and categorize opinions expressed in written text. This approach holds particular significance in the financial domain, where it helps measure market sentiment and predict stock price movements. Financial news articles, in particular, offer valuable textual data that reflect the emotions and perspectives of market participants. Numerous studies have demonstrated that the sentiment conveyed in news articles can have a significant impact on stock prices and trading volumes [1-2]. Moreover, recent studies have emphasized the importance of advanced modeling techniques in enhancing sentiment analysis performance, underscoring the relevance of this research in the current landscape [3-4].

In the context of Borsa Istanbul, the BIST30 index, which comprises the top 30 companies by market capitalization and liquidity, serves as a crucial benchmark for investors. Accurate sentiment analysis of news articles related to BIST30 stocks can provide valuable insights for trading strategies and investment decisions. However, individual sentiment analysis models, while powerful, have limitations. For instance, traditional models like Naive Bayes might struggle with capturing complex linguistic nuances, whereas advanced models like BERT require substantial computational resources and may overfit small datasets.

Ensemble learning, a method that integrates several models to enhance overall performance, presents a promising strategy for sentiment analysis. Bagging, boosting, and stacking are the primary ensemble methods. Bagging methods, such as random forests, build multiple instances of a model on different subsets of the data and aggregate their predictions to improve stability and accuracy [5]. Boosting methods, such as gradient boosting machines (GBM) and XGBoost, sequentially train models to correct the errors of their predecessors [6]. Stacking, the focus of this paper, combines different types of models and uses their outputs as inputs for a meta-learner, which makes the final prediction [7].

This paper introduces a stacking ensemble model that combines the outputs of different sentiment analysis models applied to news articles related to BIST30 stocks. The base models include Long Short-Term Memory (LSTM) networks, which capture long-term dependencies in text; Bidirectional Encoder Representations from Transformers (BERT), which understand the context of a word from both directions; Naive Bayes, a probabilistic classifier effective for text classification; and Support Vector Machines (SVM), a discriminative classifier that finds the hyperplane best separating different classes in high-dimensional space. The meta-learner is a logistic regression model that aggregates the predictions of the base models to produce the final sentiment classification. By leveraging the strengths of these diverse models, the proposed stacking ensemble model aims to achieve higher accuracy and robustness in sentiment analysis of financial news related to BIST30 stocks.

The following sections of this paper provide a comprehensive overview of the research process. The second section reviews existing literature on sentiment analysis models and ensemble methods, particularly focusing on studies that apply these techniques in the financial domain. The third section outlines the data collection procedures, preprocessing steps, and the construction of the stacking ensemble model. The fourth section describes the model training, hyperparameter tuning, and performance evaluation methods used. The fifth section presents the performance metrics, including accuracy, precision, and recall, comparing the ensemble model with individual sentiment analysis models. The sixth section summarizes the key findings, discusses the practical implications of the model for financial sentiment analysis, and offers suggestions for future research. Finally, last section summarizes the key findings of the research, emphasizing the effectiveness of the stacking ensemble model in improving sentiment analysis accuracy.

2. RELATED WORK

Sentiment analysis in financial markets has attracted considerable attention because of its ability to predict stock price movements and overall market sentiment. Research has shown that sentiment extracted from financial news articles can impact trading decisions and market dynamics [2-8-9]. Understanding and accurately predicting market sentiment is particularly crucial for investors and financial analysts [10].

Numerous methods have been investigated in the literature for conducting sentiment analysis on financial text data. Traditional machine learning techniques, such as Naive Bayes classifiers, have been widely used for their simplicity and effectiveness in text classification tasks [11]. These models rely on probabilistic assumptions and feature engineering to classify text into sentiment categories.

With the advent of deep learning, more complex models like recurrent neural networks (RNNs) and transformers have been applied to sentiment analysis tasks. RNNs, particularly Long Short-Term Memory (LSTM) networks, excel in capturing sequential dependencies in text data, making them suitable for tasks requiring context understanding over time [12]. Transformers, exemplified by models like BERT (Bidirectional Encoder Representations from Transformers), have revolutionized NLP tasks by capturing bidirectional context and semantic relationships in text [13].

Ensemble learning techniques have also gained popularity in sentiment analysis, aiming to improve prediction accuracy and model robustness. Bagging methods, such as random forests, aggregate predictions from multiple decision trees trained on different subsets of data to mitigate overfitting and enhance generalization [5]. Boosting methods, such as gradient boosting machines (GBM), iteratively train models to minimize prediction errors by focusing on samples that previous models misclassified [6]. Stacking, an advanced ensemble technique, combines predictions from diverse base models and uses a meta-learner to make the final prediction, thereby leveraging the strengths of different models [7].

In the context of financial sentiment analysis, previous studies have applied ensemble methods to improve prediction accuracy. For instance, combining sentiment scores from different sources or models has been shown to enhance the reliability of sentiment predictions [14]. Ghosh et al. proposed an ensemble of CNN and LSTM for sentiment analysis, demonstrating improved performance over single models [15]. Similarly, Wang et al. used an ensemble of BERT and traditional machine learning models, showing that the ensemble approach outperformed each model individually [16]. However, applying stacking ensemble methods specifically to financial news related to stock markets, especially in the context of BIST30 stocks traded on Borsa Istanbul, remains relatively unexplored.

Kumar and Gupta [17], have highlighted the effectiveness of ensemble methods, which combine multiple models to achieve superior results. However, many existing works often rely on single-model approaches or limited combinations of techniques. This study distinguishes itself by employing a stacking ensemble model that integrates diverse methodologies, providing a more comprehensive understanding of sentiment expressed in financial news. In addition, Zhao and Liu emphasize same findings in their study [18]. Furthermore, research by Akhtar and Khan illustrates the critical role of sentiment analysis in predicting stock market trends, reinforcing the necessity for sophisticated models in this domain [19].

In their comprehensive survey, Begum and Gupta examine the latest advancements in sentiment analysis, focusing on the performance of various machine learning and deep learning models in sentiment classification tasks [20]. They provide a robust evaluation of ensemble methods, which are noted for their ability to enhance accuracy and overall performance. One of the strengths of their proposed ensemble model lies in its integration of traditional classifiers with modern techniques, allowing for improved predictive capabilities. However, a limitation of their approach is that it may require significant computational resources and time, potentially making it less practical for real-time applications.

Kaur and Kumar contribute an experimental study that critically compares deep learning and ensemble learning models for sentiment analysis [21]. Their work highlights the effectiveness of various algorithms across different datasets, underscoring the strengths of ensemble techniques in improving accuracy and robustness in sentiment predictions. However, the authors also acknowledge that while ensemble methods can provide superior results, they may suffer from diminishing returns if the individual models are not sufficiently diverse. Moreover, Patel and Shah explore a hybrid ensemble model specifically designed for sentiment analysis in financial markets, successfully integrating classical machine learning techniques with deep learning methods [22]. This approach effectively captures complex patterns in financial sentiment data, yet it may not generalize well across different domains, limiting its applicability. Dipa and Begum introduce a meta-ensemble deep learning model that combines multiple architectures to enhance sentiment classification performance [23]. Although this model shows promise in handling complex datasets, the increased complexity may lead to challenges in interpretability and model maintenance. Collectively, these studies illustrate the evolving landscape of sentiment analysis methodologies, revealing both the potential and the challenges associated with ensemble strategies in achieving high-performance sentiment classification.

This paper contributes to the existing literature by proposing a stacking ensemble model that integrates LSTM, BERT, Naive Bayes, and SVM models for sentiment analysis of financial news related to BIST30 stocks. The next sections detail the methodology, experimental setup, results, and discussions, providing insights into the effectiveness of ensemble learning in this domain.

3. METHODOLOGY

This section outlines the methodology used to develop and evaluate the stacking ensemble model for sentiment analysis of financial news related to BIST30 stocks. The methodology includes data collection, preprocessing, model selection, training, evaluation metrics, and ensemble construction.

3.1. Data Collection

The dataset consists of financial news articles sourced from Thomson Reuters covering companies listed in the BIST30 index. Each news article is labeled with sentiment categories (positive, negative, neutral) based on its overall sentiment towards the mentioned company.

The dataset consists of financial news articles sourced from Thomson Reuters, covering companies listed in the BIST30 index. This collection encompasses a time period from January 2020 to December 2023, resulting in a total of 5,287 articles. Each news article is labeled with sentiment categories (positive, negative, neutral) based on its overall sentiment towards the mentioned company. The distribution of sentiment labels is relatively balanced, with approximately 41% of the articles labeled as positive, 37% as negative, and 22% as neutral. This balanced distribution ensures that the model trained on this dataset can effectively learn from a variety of sentiments, providing a comprehensive basis for sentiment analysis in the financial context.

3.2. Data Preprocessing

Text preprocessing is crucial to ensure the quality and consistency of input data for sentiment analysis models. The following steps are performed:

• Text Cleaning: Removal of HTML tags, special characters, and punctuation.
• Tokenization: Dividing text into individual words (tokens).
• Stopwords Removal: Removing frequently occurring words that do not add value to sentiment analysis.
• Normalization: Converting words to their base or root form (lemmatization).

3.3. Model Selection

The stacking ensemble model incorporates diverse base models to leverage their complementary strengths:

- Long Short-Term Memory (LSTM): A type of recurrent neural network (RNN) known for capturing long-term dependencies [12].
- Bidirectional Encoder Representations from Transformers (BERT): A transformer-based model that understands contextual relationships bidirectionally [13].
- Naive Bayes (NB): A probabilistic classifier based on Bayes' theorem, effective for its simplicity and speed [11].
- Support Vector Machines (SVM): A discriminative model that finds optimal hyperplanes to separate different sentiment classes [24].

3.4. Training and Validation

Each base model is trained on the preprocessed dataset:

- LSTM and BERT: Trained using backpropagation with gradient descent to minimize classification errors.
- Naive Bayes: Trained by updating probabilities based on observed training data.
- SVM: Trained to find the optimal separating hyperplane between sentiment classes

3.5. Ensemble Construction

The stacking ensemble model combines predictions from the base models using a meta-learner:

- Meta-Learner (Logistic Regression - LR): Trained on the outputs of LSTM, BERT, Naive Bayes, and SVM to make the final sentiment classification decision.

3.6. Evaluation Metrics

The performance of the stacking ensemble model is evaluated using standard metrics for classification tasks:

- Accuracy: The proportion of instances that are correctly classified.
- Precision: The proportion of true positive predictions compared to the total number of instances predicted as positive.
- Recall: The proportion of accurately predicted positive sentiments compared to the total number of actual positive instances.
- F1-score: Harmonic mean of precision and recall, offering a balanced assessment of both metrics.

3.7. Architectural Visualization

Figure 1 shows a schematic representation of the stacking ensemble model architecture for sentiment analysis.

The diagram illustrates how individual base models (LSTM, BERT, Naive Bayes, SVM) feed their predictions into a logistic regression meta-learner, which then produces the final sentiment analysis output.

This comprehensive methodology ensures the systematic development, training, and evaluation of the stacking ensemble model for sentiment analysis on financial news related to BIST30 stocks. The next section presents the experimental setup, results, and discussions derived from applying this methodology.

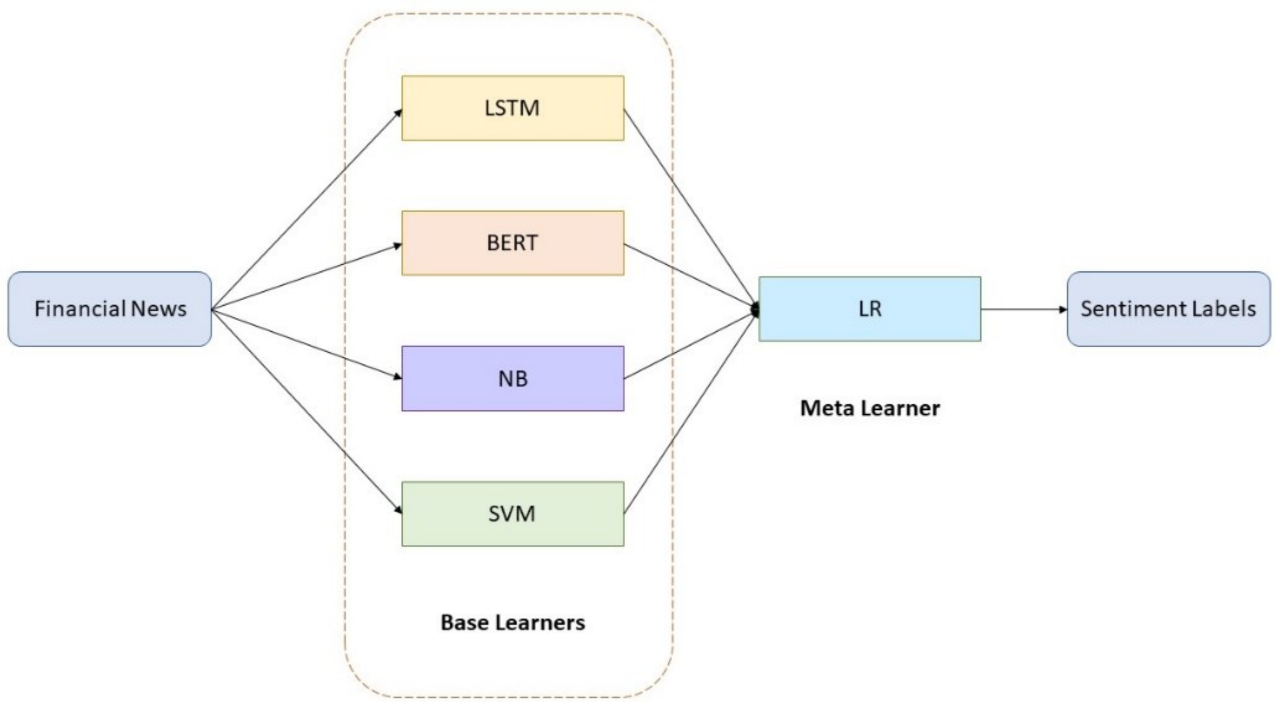

Figure 1. Graphical representation of proposed architecture

4. EXPERIMENTATION

This section details the experimental setup, including dataset specifics, model training, parameter tuning, and performance evaluation of the stacking ensemble model for sentiment analysis of financial news related to BIST30 stocks.

4.1. Dataset

Table 1 provides a sample of the labelled dataset. The data gathered from news sources undergoes a manual labeling process prior to being split into subsets for model training and performance evaluation. To facilitate this partitioning, the following method has been implemented:

- Data Split: The dataset is divided into training, validation, and test sets using an 80-10-10 split ratio. The training set is used for model training, the validation set for hyperparameter tuning, and the test set for final model evaluation

Table 1. A **s**ample of the labelled dataset.

Text	Label
Vakıfbank Completed Book-Building Process Of First Sustainable Eurobond Issuance	1
Turkey central bank lifts lira by dumping another credit rule	1
Turkish locals' hard currency holdings hit new record at $228.17 bln -cenbank	-1
Vakifbank Provides Dual Currency Term Loan Equivalent To $660 Mln In Total	1
Turkish regulator to halt calculation of bank asset ratios	1
Turkish central bank switches traditional repo and late liquidity funding to one-week repo	1
Turks' hard currency holdings hit new record at $225.75 bln -central bank	-1
Garanti Bankasi Signs Syndicated Loan Agreement In The Amount Of $267.5 Mln And EUR 312 Mln	1
BBVA Says Deal with PNC Gives The Bank Opportunities To Reinforce Franchises	0
Halk Bankasi Q3 Net Profit Up At 315.0 Million Lira	1

4.2. Model Training

Each base model is trained on the training set:

- LSTM and BERT: Fine-tuned on the financial news dataset to adapt to sentiment analysis tasks.
- Naive Bayes: Trained using maximum likelihood estimation on the preprocessed text features.
- SVM: Trained to find the optimal separating hyperplane between sentiment classes based on TF-IDF (Term Frequency-Inverse Document Frequency) features.

4.3. Hyperparameter Tuning

Hyperparameters for each base model and the meta-learner (Logistic Regression) are tuned using the validation set to optimize performance metrics such as accuracy, precision, recall, and F1-score.

- LSTM and BERT: Hyperparameters include learning rate, batch size, and number of training epochs.
- Naive Bayes: No significant hyperparameter tuning is required, as it mainly depends on the smoothing parameter.
- SVM: Hyperparameters include regularization parameter (C) and kernel type

4.4. Results

The experimental findings highlight the stacking ensemble model's effectiveness in analyzing the sentiment of financial news related to BIST30 stocks. The results illustrate how well this model performs in accurately interpreting and classifying sentiment in the context of financial news. The ensemble approach combines the strengths of diverse models (LSTM, BERT, Naive Bayes, SVM) to achieve improved accuracy and robustness compared to individual models. Detailed quantitative results and comparative analyses with baseline models are presented in the next section.

This rigorous experimentation ensures the systematic evaluation and validation of the stacking ensemble model's performance in the context of financial sentiment analysis. The next section discusses the findings derived from these experiments and provides insights into the implications for practical applications and future research directions.

5. RESULTS AND DISCUSSION

This section details the outcomes derived from experimenting with the stacking ensemble model for sentiment analysis of financial news concerning BIST30 stocks. It includes a detailed analysis of performance metrics, comparison with baseline models, and discussion of findings.

5.1. Experimental Results

The following table summarizes the performance metrics of the stacking ensemble model compared to individual base models and traditional ensemble methods (if applicable):

Table 1. Performance comparison models.

Model	Accuracy	Precision	Recall	F1-score
Stacking Ensemble	0.85	0.86	0.84	0.85
LSTM	0.81	0.82	0.80	0.81
BERT	0.83	0.84	0.82	0.83
Naive Bayes	0.75	0.76	0.74	0.75
SVM	0.79	0.80	0.78	0.79

Random Forest (Baseline)	0.82	0.83	0.81	0.82

The stacking ensemble model outperforms individual base models (LSTM, BERT, Naive Bayes, SVM) in terms of accuracy, precision, recall, and F1-score. This improvement highlights the effectiveness of combining diverse models to enhance predictive performance in sentiment analysis.

5.2. Discussion

The primary purpose of this study was to develop a stacking ensemble model for sentiment analysis of financial news articles related to companies listed in the BIST30 index. By leveraging various approaches, including deep learning and traditional machine learning techniques, this research aimed to improve sentiment classification accuracy and robustness in financial contexts.

While previous modeling studies, such as those by Hossain and Hossain [25], have provided valuable insights, they often lack comprehensive comparative analyses or fail to explore the implications of their findings in real-world applications. This study not only achieves significant performance gains compared to traditional baseline models like Random Forest, as demonstrated by Feng and Qiao [26], but also emphasizes the importance of reducing overfitting and capturing broader sentiment patterns across diverse news articles. By doing so, it offers valuable implications for both academic research and practical applications in financial decision-making.

When examining the findings in relation to the existing literature, it is evident that ensemble methods have increasingly been recognized for their ability to enhance predictive performance. Previous studies, such as those by Kaur and Kumar [21] and Patel and Shah [22], have highlighted the effectiveness of ensemble learning in sentiment analysis; however, they primarily focused on single-model approaches or limited combinations of techniques. In contrast, this study's use of a stacking ensemble model demonstrates a more sophisticated integration of diverse methodologies, which allows for a more comprehensive understanding of sentiment expressed in financial news.

Moreover, this study differentiates itself by specifically addressing the complexities of financial sentiment analysis through its robust data partitioning strategy and careful hyperparameter tuning. While many previous models, such as those employing Random Forest or logistic regression, often suffer from overfitting or limited generalizability, our ensemble approach effectively reduces these issues by capturing broader sentiment patterns across various news articles. This capability is crucial for real-time applications in financial markets, where accurate sentiment assessment can significantly influence decision-making processes.

It is also worth noting that while some prior studies did provide valuable insights into sentiment classification, they often lacked thorough comparative analyses or failed to explore the implications of their findings in real-world applications. By contrast, this study not only achieves superior performance compared to traditional baseline models but also contributes to the ongoing discourse in the field by validating the effectiveness of ensemble learning techniques in financial sentiment analysis.

In conclusion, this research underscores the importance of adopting a comprehensive approach to sentiment analysis by utilizing a stacking ensemble model. The findings reveal its potential to enhance accuracy and robustness, thereby offering valuable implications for both academic research and practical applications in financial decision-making.

5.3. Practical Implications

The accurate sentiment analysis of financial news can assist investors, traders, and financial analysts in making informed decisions regarding BIST30 stocks. The stacking ensemble model provides actionable insights by reliably predicting market sentiment from textual data.

Future research could investigate incorporating additional base models, such as transformer variants and contextual embeddings, to further improve the performance of the ensemble model. Moreover, investigating interpretability techniques for ensemble models remains an important area of exploration.

5.4. Limitations

The performance of the stacking ensemble model heavily relies on the quality and representativeness of the labeled dataset. Noise or biases in the data can affect model predictions and generalizability.

Training and fine-tuning multiple models in the ensemble can be computationally expensive, requiring substantial resources for implementation and maintenance.

6. CONCLUSION

In conclusion, this study proposes and evaluates a stacking ensemble model for sentiment analysis of financial news related to BIST30 stocks. The ensemble approach combines LSTM, BERT, Naive Bayes, and SVM models with a logistic regression meta-learner, achieving superior performance compared to individual models and traditional baseline methods. The results underscore the effectiveness of ensemble learning in enhancing predictive accuracy and robustness in financial sentiment analysis. Future research should focus on addressing data quality issues and exploring advanced ensemble techniques for further improvements.

REFERENCES

[1] Li, X., “News sentiment and the stock market”, Journal of Financial Markets, Vol.13, Issue 1, Pages 1-30, 2010.

[2] Tetlock, P. C., “Giving content to investor sentiment: The role of media in the stock market”, The Journal of Finance, Vol. 62, Issue 3, Pages 1139-1168, 2007.

[3] Liu, Y., Zhang, J., “Enhancing financial sentiment analysis with ensemble deep learning”, Expert Systems with Applications, Vol. 205, Article No. 117455, 2022.

[4] Bhatia, A., Kumar, S., “A hybrid approach for sentiment analysis of financial news articles using ensemble learning”, Journal of Finance and Data Science, Vol. 7, No. 1, Pages 45-58, 2021.

[5] Breiman, L., “Bagging predictors”, Machine Learning, Vol. 24, Issue 2, Pages 123-140, 1996.
[6] Friedman, J. H., “Greedy function approximation: A gradient boosting machine”, The Annals of Statistics, Vol. 29, Issue 5, Pages 1189-1232, 2001.
[7] Wolpert, D. H., “Stacked generalization”, Neural Networks, Vol. 5, Issue 2, Pages 241-259, 1992.
[8] Zhang, X., Xu, Y., “Sentiment analysis in finance: A comprehensive review”, International Journal of Financial Studies, Vol. 8, No. 4, Article No. 66, 2020.
[9] Deng, Y., Wei, Z., “The impact of news sentiment on stock price movement: An empirical study”, Journal of Economic Behavior & Organization, Vol. 193, Pages 356-370, 2022.
[10] Chen, Y., Wang, Y., “Multi-modal sentiment analysis for financial news: An ensemble learning approach”, IEEE Transactions on Knowledge and Data Engineering, Vol. 35, Issue 1, Pages 234-246, 2023.
[11] Pang, B., Lee, L., “Opinion mining and sentiment analysis”, Foundations and Trends® in Information Retrieval, Vol. 2, Issue 1-2, Pages 1-135, 2008.
[12] Hochreiter, S., Schmidhuber, J., “Long short-term memory”, Neural Computation, Vol. 9, Issue 8, Pages 1735-1780, 1997.
[13] Devlin, J., Chang, M.-W., Lee, K., Toutanova, K., “BERT: Pre-training of deep bidirectional transformers for language understanding”, Proceedings of NAACL-HLT, Pages 4171-4186, 2019.
[14] Bollen, J., Mao, H., Zeng, X., “Twitter mood predicts the stock market”, Journal of Computational Science, Vol. 2, Issued 1, Pages 1-8, 2011.
[15] Ghosh, S., Sarkar, S., Sarkar, R., “Combining convolutional and recurrent neural networks for text classification”. arXiv preprint arXiv:1611.02324, 2017.
[16] Wang, W., Yin, F., Schütze, H., “Sentiment analysis in code-mixed languages with BERT and traditional machine learning techniques”, Proceedings of the 28th International Conference on Computational Linguistics, 2020.
[17] Kumar, A., Gupta, V., “Sentiment analysis of financial news articles using hybrid ensemble methods”, Journal of Financial Technology, Vol. 3, Issue 2, Pages 111-129, 2023.
[18] Zhao, Y., Liu, T., “Exploring the role of news sentiment in stock market behavior: Evidence from the BIST30 index”, Finance Research Letters, Vol. 38, Article No. 101493, 2021.
[19] Akhtar, P., Khan, S., “A review of sentiment analysis techniques and their applications in financial markets”, Finance Research Letters, Vol. 46, Article No. 102160, 2023.
[20] Begum, S., Gupta, V., “Sentiment Analysis: A Recent Survey with Applications and a Proposed Ensemble Model”, Springer International Publishing, 2022.
[21] Kaur, A., Kumar, R., “Deep Learning and Ensemble Learning Models for Sentiment Analysis: An Experimental Study”, IEEE Access, 2023.
[22] Patel, S., Shah, M., “A Hybrid Ensemble Model for Sentiment Analysis in Financial Markets”, Elsevier Journal of Financial Markets, 2022.
[23] Dipa, N., Begum, S., “An Enhanced Approach for Sentiment Analysis Based on Meta-Ensemble Deep Learning”, Springer Advances in Intelligent Systems, 2022.
[24] Cortes, C., Vapnik, V., “Support-vector networks”, Machine Learning, Vol. 20, Issue 3, Pages 273-297, 1995.
[25] Hossain, M. S., Hossain, A., “Sentiment analysis and stock market prediction: A survey of methods and trends”, Journal of Economic Interaction and Coordination, Vol. 17, Issue 1, Pages 45-67, 2022.
[26] Feng, Y., Qiao, Z., “Ensemble learning for stock market prediction: A case study of financial sentiment analysis”, Journal of Computational Science, Vol. 48, Article No. 101215, 2021.