Scientific Research Publishing

Journal of Data Analysis and Information Processing, 2025, 13(3), 269-280
https://www.scirp.org/journal/jdaip
ISSN Online: 2327-7203
ISSN Print: 2327-7211

Comparative Research in Sentiment Analysis Using Machine Learning Technique

Eun Soo Park, Rushit Dave, Mansi Bhavsar

Department of Computer Information Science, Minnesota State University, Mankato, MN, USA
Email: rushit.dave@mnsu.edu

How to cite this paper: Park, E.S., Dave, R., and Bhavsar, M. (2025) Comparative Research in Sentiment Analysis Using Machine Learning Technique. *Journal of Data Analysis and Information Processing*, **13**, 269-280.
https://doi.org/10.4236/jdaip.2025.133016

Received: June 24, 2025
Accepted: July 28, 2025
Published: July 31, 2025

Abstract

In today's digital background, sentiment analysis has become an essential factor of Natural Language Processing (NLP), offering valuable insights from vast online data sources. This paper presents a comparative analysis of sentiment analysis techniques leveraging machine learning. As digital content continues to expand rapidly, decoding public sentiment has become increasingly important for businesses and researchers. The study examines various approaches, including traditional machine learning methods like Support Vector Machines (SVM) and Naïve Bayes (NB), as well as deep learning models such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks. It also explores hybrid frameworks that combine the strength of both paradigms. By evaluating the advantages and limitations of these models, especially within the context of e-commerce, this review provides a comprehensive understanding of their performance. Additionally, the paper addresses critical challenges such as real-time sentiment detection and multi-label classification. Through a synthesis of existing research, it highlights promising directions for future work and contributes to the development of more accurate and practical sentiment analysis solutions across various applications.

Keywords

Sentiment Analysis, Machine Learning, Deep Learning

1. Introduction

In this digital age, as people increasingly rely on the Internet to share their thoughts and opinions, sentiment analysis has become a crucial aspect of Natural Language Processing (NLP). Social media platforms like Twitter, Instagram, Reddit, and Facebook serve not only as communication channels but also as valuable sources for understanding public sentiment [1]. Whether businesses aim to refine their marketing strategies or researchers seek to detect fake news, extracting meaningful insights from textual data is essential [2]. As the amount of digital content rapidly expands, leveraging sentiment analysis enables us to interpret trends, distinguish genuine from misleading information, and make data-driven decisions [3].

To effectively analyze sentiments expressed in digital content, various machine learning and deep learning approaches have been developed. Sentiment analysis techniques determine the sentiment polarity of text—whether it is positive, negative, or neutral [4]. By utilizing natural language processing methods such as tokenization, word embeddings, and sentiment lexicons, these models can analyze a vast amount of textual data with high accuracy [5]. Businesses and organizations rely on sentiment analysis to gain valuable insights into customer feedback, brand perception, and market trends [6]. Advanced deep learning architectures such as Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks further enhance the ability to capture contextual meaning and sentiment nuances. As sentiment analysis continues to evolve, it plays an increasingly important role in optimizing marketing strategies, improving customer experience, and detecting misinformation in digital content [7].

This paper reviews the advancements in sentiment analysis, evaluating different methodologies and their effectiveness across existing research studies. By comparing machine learning-based, deep learning-based and hybrid approaches, this study aims to provide insights into how different models can enhance decision-making, improve text classification accuracy, and optimize sentiment-based applications. Additionally, this study identifies limitations of different models, offering promising directions for future research.

The following sections provide an overview of sentiment analysis trends, as well as a comprehensive literature review summarizing methodologies and applications of existing research. Finally, this paper discusses the challenges of current sentiment analysis research and concludes with insights into future directions.

2. Background

Over the past decade, sentiment analysis has evolved from simple text classification techniques to sophisticated machine learning and deep learning models. Early approaches primarily relied on lexicon-based and rule-based methods, which struggled to capture the nuances of human sentiment. However, the growing availability of large-scale labeled datasets enabled the adoption of supervised and unsupervised learning techniques, improving sentiment classification accuracy. Recent trends emphasize enhancing model performance for multilingual and cross-domain applications and improving the interpretability of AI-based sentiment classification. Studies have also explored various deep learning architectures, such as Bidirectional Encoder Representations from Transformers (BERT) models [8] and recursive deep models [9], to better understand sentiment in complex textual data. Additionally, sentiment analysis has been applied to a wide range of fields, including e-commerce [10] and social media, highlighting its versatility and impact on decision-making processes.

This literature review explores several research questions, such as:

- How can machine learning-based customer sentiment analysis of reviews be used to recommend shoppers and shops?
- How can real-time sentiment analysis be applied to e-commerce applications?
- How can machine learning be used for multi-label classification of e-commerce customer reviews?

In the subsequent sections, this review delves into these questions, comparing existing methodologies and applications to provide insights into improving sentiment analysis models for e-commerce.

3. Methodology

This literature review was conducted through a systematic search of major academic databases, including IEEE Xplore, ACM Digital Library, ScienceDirect, and Google Scholar. The research strategy employed key terms such as "sentiment analysis", "machine learning", "deep learning", "e-commerce", "natural language processing", and combinations thereof using Boolean operators. Studies published between 2017 and 2024 were included to capture recent advancements while maintaining focus on contemporary techniques. The inclusion criteria prioritized peer-reviewed articles, conference proceedings, and journal publications that specifically addressed sentiment analysis applications in e-commerce contexts using machine learning approaches, while excluding studies focused solely on theoretical frameworks without empirical validation.

4. Literature Review

4.1. Overview of Sentiment Analysis in E-Commerce

Sentiment analysis has become a crucial tool for understanding customer opinions and enhancing e-commerce platforms. Shathik *et al.* [11] provide a comprehensive review of sentiment analysis applications using machine learning techniques, discussing key challenges and improvements. A significant contribution is the categorization of machine learning based sentimental analysis methods, emphasizing their applications, strengths, and limitations. Chaturvedi *et al.* [12] examine sentiment analysis in business intelligence, emphasizing its role in decision-making. The paper introduces sentiment analysis as a key tool to process unstructured data, offering practical and computational insights into its application for improving decision-making processes in competitive business environments. More recently, Huang *et al.* [13] reviewed current machine learning techniques for sentiment analysis in e-commerce, highlighting their effectiveness. The study systematically reviewed 54 experimental papers on sentiment analysis in e-commerce, results show that Support Vector Machine (SVM) and Naïve Bayes (NB) were the most widely used machine learning models consistently shown better results than others, whereas Recurrent Neural Networks (RNN) and its variation like Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU) were dominant in deep learning models. The study also finds that deep learning techniques like BERT, Convolutional Neural Networks (CNN), RNN, and LSTM classification are frequently used in recent studies. Alonso *et al.* [14] explore sentiment analysis for fake news detection, comparing models like Random Forest (RF), NB, SVM, LSTM, and CNN. It discusses how fake news often contains emotionally charged language to manipulate readers and increase engagement. Various sentiment analysis techniques are evaluated, and the result shows that hybrid models outperform standalone classifiers. Kawade *et al.* [15] apply sentiment analysis to Uri attack using R for textual data processing. It highlights how sentiment analysis can mine public emotions from social media platforms like Twitter and process them for better understanding of public opinions on events.

As shown in **Figure 1**, the sentiment analysis process generally involves stages such as data collection, preprocessing, feature extraction, model training, and evaluation.

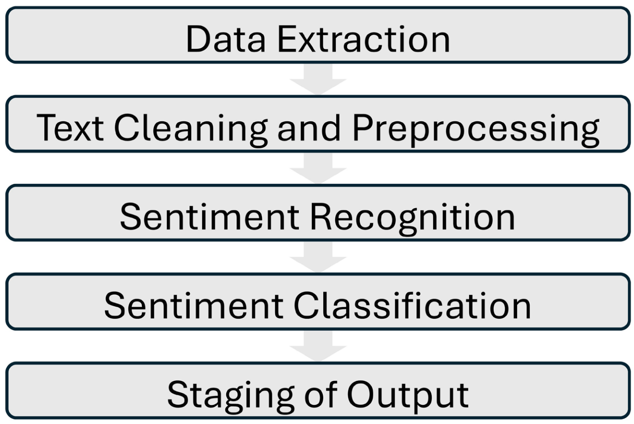

Figure 1. General sentiment analysis process pipeline.

4.2. Machine Learning Approaches for Sentiment Analysis

Building on the foundational overview of sentiment analysis techniques, several studies have implemented traditional machine learning techniques that have been widely applied for sentiment analysis in e-commerce. Yi *et al.* [16] apply multinomial NB, K-Nearest Neighbors (KNN), and SVM combined with collaborative filtering to recommend products and shops based on customer reviews, achieving improved recommendation accuracy measured by Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). By integrating collaborative filtering and product-product similarity techniques, the study provides a framework for identifying customer preferences and enhancing e-commerce experiences. Deniz *et al.* [17] introduce a multi-label classification approach using Binary Relevance, Multi-label KNN, and One-vs-Rest classifiers with Logistic Regression (LR), Stochastic Gradient Descent (SGD), and XGBoost. The best performing model was One-vs-Rest-XGBoost with 94.2% accuracy and 0.89 F1-score, indicating a low misclassification rate. Among feature extraction techniques, Term Frequency-Inverse Document Frequency (TF-IDF) performed better than word embeddings and transformers. Saura *et al.* [18] utilize SVM and Latent Dirichlet Allocation (LDA) to extract key indicators for startup business success, evaluated through topic coherence scores and classification accuracy. LDA identifies words and separates each word into a different document, randomly identifies distribution of the topics in a sample and then selects the main topics found in the sample. The identified topics are further analyzed using NVivo software to extract meaningful insight. Alnasrawi *et al.* [19] enhance sentiment classification by integrating text network features with various machine learning models, including SVM, RF, LR, NB, Decision Trees (DT), Neural Networks (NN), Gradient Boosting (GB), and AdaBoost. Among all methods, NN outperformed other models with 88.7% accuracy and 0.85 F1-score, and incorporating network-based features improved classification performance by 5% - 8% across precision, recall and F1-score metrics, particularly for NN and ensemble methods.

4.3. Deep Learning Approaches for Sentiment Analysis

Despite the effectiveness of traditional machine learning models, their limitations in handling complex linguistic patterns have led researchers to explore deep learning techniques for more nuanced sentiment classification. Deep learning techniques have been widely adopted for sentiment analysis due to their ability to capture complex language patterns. Mehta *et al.* [20] propose a CNN-based sentiment classification model enhanced with Word2Vec and TF-IDF to analyze customer reviews in the apparel sector using deep learning models, achieving 92.3% accuracy and 0.91 F1-score. The study does not evaluate other deep learning models, which could improve sentiment classification. Lin [21] employs Natural Language Processing (NLP) methods to analyze correlation between e-commerce customer review features and product recommendations. The researcher examined several different models, like Lasso Regression, Ridge Regression, Linear Kernel SVM, Radial Basis Function (RBF) Kernel SVM, RF, XGBoost, and LightGBM. The best result was achieved by LightGBM with 0.847 R-squared value and the correlation between review ratings and product recommendations was found to be strong. Kundra *et al.* [22] compare traditional machine learning models such as NB, SVM, RF, and AdaBoost with deep learning based RNN and GRU. The research results show that the best-performing model is RNN-GRU with 89.5% accuracy and 0.87 F1-score for unstructured data, but SVM achieved 91.2% accuracy for structured data analysis and performed best in both structured and unstructured data analysis, demonstrating that RNN captures the nuances of unstructured and context-rich information while traditional models excel with structured inputs.

4.4. Hybrid Approaches for Sentiment Analysis

To capitalize on the strength of both traditional and deep learning approaches, recent studies have proposed hybrid models that aim to achieve higher accuracy and adaptability in sentiment analysis. Hybrid models have been developed to enhance sentiment analysis accuracy by combining traditional machine learning and deep learning methods. Zhao *et al*. [23] introduce a new optimized machine learning algorithm called the Local Search Improvised Bat Algorithm-based Elman Neural Network (LSIBA-ENN) for sentiment analysis, a new term weighting technique called Log Term Frequency-based Modified Inverse Class Frequency (LTF-MICF) for sentiment classification, and a Hybrid Mutation-based Earthworm Algorithm (HMEWA) for feature selection. The LSIBA-ENN model achieved 95.2% accuracy and 0.94 F1-score, outperforming traditional classifiers, and the LTF-MICF weighting scheme improved performance by 3% - 5% compared to TF-IDF and Word2Vec-based approaches. There are several studies combining the CNN and LSTM methods to improve the accuracy of sentiment analysis. Vatambeti *et al*. [24] employ a ConvBiLSTM model, integrating CNN and (Bi-LSTM) with an Elephant Herd Optimization (EHO) algorithm. EHO is a swarm-based optimization method used to optimize the weight of the Bi-LSTM, deep learning model parameters. The Optimized model achieved 93.8% accuracy with 0.92 precision and 0.91 recall on Twitter food service data. Behera *et al*. [25] present Co-LSTM, a combination of CNN and LSTM, for sentiment classification in social media data. The proposed model achieved 94.5% accuracy and 0.93 F1-score, outperforming standalone CNN with 87.2% accuracy and LSTM with 89.7% accuracy. The model is highly adaptable in examining big social data and is free from any particular domain, unlike conventional machine learning approaches. Co-LSTM performed particularly well on long and complex texts by effectively capturing dependencies between words. Ray *et al*. [26] also integrated CNN with rule-based methods to improve aspect-level sentiment analysis. The model achieved 88.4% accuracy and 0.86 F1-score, incorporating hierarchical clustering and dependency parsing to refine aspect categorization and improve accuracy. Jain *et al*. [27] implemented a CNN-LSTM model for consumer sentiment analysis and the model demonstrated 91.7% accuracy with 0.89 precision and 0.88 recall, higher than standalone deep learning and machine learning models. Furthermore, Priyadarshini *et al*. [28] develop a hybrid LSTM-CNN model with Grid Search Optimization. The model achieved the highest performance with 96.1% accuracy, 0.95 precision, 0.94 recall, and 0.94 F1-score. The model is compared with baseline algorithms, including CNN (88.2% accuracy), KNN (82.1% accuracy), LSTM (90.3% accuracy), CNN-LSTM (92.8% accuracy) and LSTM-CNN (93.4% accuracy), and LSTM-CNN-Grid Search achieved higher performance as the research incorporated grid search as a hyperparameter optimization technique to minimize pre-defined losses.

As illustrated in **Figure 2**, the machine learning workflow for sentiment analysis often integrates various stages, including data input, feature extraction, model selection, and performance evaluation.

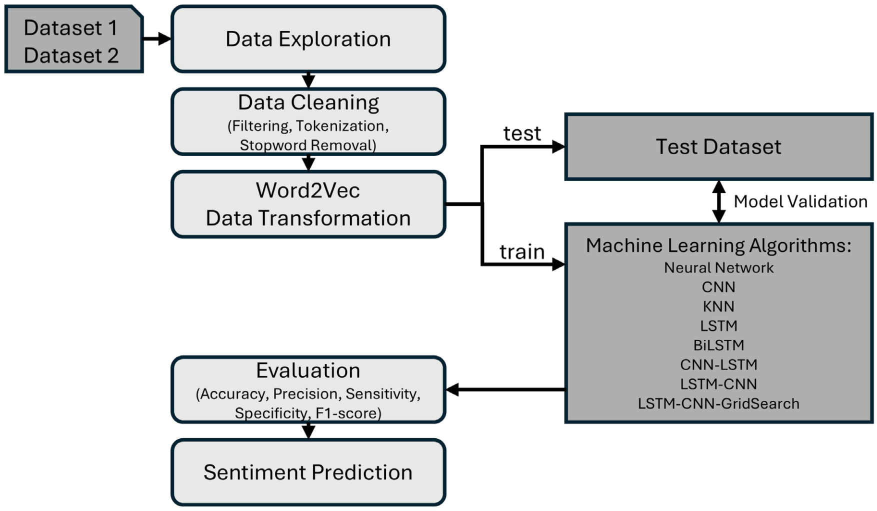

Figure 2. An example of machine learning workflow for sentiment analysis.

4.5. Real-Time Application

As sentiment analysis techniques continue to evolve, there is growing interest in applying these models in real-time systems to provide immediate feedback and actionable insights. Several studies focus on real-time sentiment analysis and AI-driven emotion visualization. Jabbar *et al.* [29] implement a SVM-based real-time sentiment analysis system within a mobile application using Python and Flask. The system achieved 87.3% accuracy with an average response time of 0.8 seconds per query. When users submit a review, the application processes the text through the model, which predicts the sentiment polarity and provides immediate feedback. Li *et al.* [30] propose an explanation framework for AI-driven sentiment analysis, leveraging Bi-LSTM with attention mechanisms to visualize emotion-triggering words. The proposed framework achieved 91.2% accuracy and 0.88 F1-score while providing 78% user satisfaction in explainability surveys. The framework emphasizes considering the cause and trigger of emotions as the explanation for the deep learning-based emotion analysis. The proposed method has more functionality, usability, reliability, and performance compared to SHapley Additive exPlanations (SHAP), which is a model interpretation package developed by Python and Local Interpretable Model-agnostic Explanations (LIME) which is an explainable framework for black box deep learning models using a local explainable model to explain each separate prediction, with 15% higher user comprehension scores and 20% faster explanation generation time.

This literature review highlights the diverse methodologies utilized in sentiment analysis, including traditional machine learning, deep learning, hybrid approaches, and real-time applications, reflecting the dynamic evolution of sentiment analysis in e-commerce. Together, these developments from traditional machine learning to real-time deep learning systems highlight the dynamic landscape of sentiment analysis in e-commerce, underscoring its critical role in enhancing user engagement, personalization, and business intelligence.

4.6. Comparative Analysis Table of Sentiment Analysis Studies

Study	Dataset	Model Type	Domain	Best Performing Model	Best Metric
Shathik *et al.* [11]	Multiple datasets	ML/DL Review	General Review Paper	N/A	N/A
Chaturvedi *et al.* [12]	Business data	ML	Business Intelligence	N/A (Framework)	N/A
Huang *et al.* [13]	54 studies meta-analysis	ML/DL Review	E-commerce	SVM, NB, LSTM, GRU	Accuray and F1-score (Review paper)
Alonso *et al.* [14]	Fake news datasets	ML/DL/Hybrid	Fake News Detection	Hybrid models	Accuracy, Precision, Recall, F1-score
Kawade *et al.* [15]	Twitter data (Uri attack)	ML	Social Media/Events	N/A	N/A
Yi *et al.* [16]	Customer reviews	ML + Collaborative Filtering	E-commerce Recommendation	Multinomial NB + Collaborative Filtering	MAE, RMSE improvement
Deniz *et al.* [17]	E-commerce customer reviews	Multi-label ML	E-commerce	One-vs-Rest-XGBoost	94.2% Accuracy, 0.89 F1-score
Saura *et al.* [18]	Startup business data	SVM + LDA	Business/Startup	SVM + LDA	Topic coherence & classification accuracy
Alnasrawi *et al.* [19]	Text network data	ML Ensemble	General	Neural Networks	88.7% Accuracy, 0.85 F1-score
Mehta *et al.* [20]	Apparel sector reviews	CNN + Word2Vec/ TF-IDF	E-commerce (Apparel)	CNN with Word2Vec/ TF-IDF	92.3% Accuracy, 0.91 F1-score
Lin [21]	E-commerce reviews	ML/Regression	E-commerce	LightGBM	0.847 R-squared
Kundra *et al.* [22]	Structured/ unstructured data	ML/DL	General	RNN-GRU (unstructured), SVM (structured)	RNN-GRU: 89.5% Accuracy, 0.87 F1-score; SVM: 91.2% Accuracy
Zhao *et al.* [23]	Product reviews	Hybrid (LSIBA-ENN)	E-commerce	LSIBA-ENN with LTF-MICF	95.2% Accuracy, 0.94 F1-score
Vatambeti *et al.* [24]	Twitter food service data	ConvBiLSTM + EHO	Social Media/Food	ConvBiLSTM with EHO optimization	93.8% Accuracy, 0.92 Precision, 0.91 Recall
Behera *et al.* [25]	Social media data	Co-LSTM (CNN + LSTM)	Social Media	Co-LSTM	94.5% Accuracy, 0.93 F1-score

Continued

Ray *et al.* [26]	Aspect-level data	CNN + Rule-based	Aspect-level Analysis	CNN with rule-based integration	88.4% Accuracy, 0.86 F1-score
Jain *et al.* [27]	Consumer data	CNN-LSTM	Consumer Analysis	CNN-LSTM	91.7% Accuracy, 0.89 Precision, 0.88 Recall
Priyadarshini *et al.* [28]	General sentiment data	LSTM-CNN + Grid Search	General	LSTM-CNN with Grid Search	96.1% Accuracy, 0.95 Precision, 0.94 Recall, 0.94 F1-score
Jabbar *et al.* [29]	Mobile app reviews	SVM	Real-time E-commerce	SVM (real-time)	87.3% Accuracy, 0.8s response time
Li *et al.* [30]	Emotion analysis data	Bi-LSTM + Attention	AI Explanation/ Visualization	Bi-LSTM with attention	91.2% Accuracy, 0.88 F1-score, 78% user satisfaction

5. Limitations

Despite the advancements in sentiment analysis methodologies, several limitations persist in the current research. One major challenge lies in the implementation of real-time sentiment analysis systems. While real-time sentiment analysis applications are gaining traction, as evidenced by Jabbar *et al.* [29], the generalizability and robustness of real-time sentiment analysis models in handling diverse, high-volume data streams remain a challenge. Furthermore, the explanation frameworks for AI-driven emotion visualization, like those proposed by Li *et al.* [30], are promising but are still in their early stages and require further validation in real-world scenarios to ensure reliability and usability.

Also, the literature highlights the increasing adoption of multi-label classification approaches for sentiment analysis, as seen in Deniz *et al.* [17], which addresses the complexity of customer reviews containing multiple sentiments. However, the evaluation and comparison of these multi-label models are often conducted on specific e-commerce datasets, limiting the broader applicability of the findings. The performance of multi-label classifiers can vary significantly depending on the dataset's characteristics, such as label distribution and text complexity. Additionally, the feature extraction techniques employed in these studies are effective but may not fully capture the nuanced relationships between different sentiment labels, leading to suboptimal model generalization across platforms or domains.

6. Conclusions and Future Work

This paper has reviewed the significant advancements and methodologies in sentiment analysis, particularly within the context of e-commerce. The evolution from traditional machine learning techniques to sophisticated deep learning and hybrid models demonstrates the potential of sentiment analysis to enhance decision-making processes in various applications. The findings indicate that while deep learning architectures, such as RNNs and BERT, have shown remarkable performance in capturing contextual nuances, traditional models like SVM and Naïve Bayes remain relevant for specific tasks, particularly in cases with limited data.

Despite these advancements, several limitations persist, notably in the areas of real-time analysis, multi-label classification, and the interpretability of AI-driven models. The challenge of generalizing sentiment analysis models across diverse datasets and the need for robust frameworks to visualize emotions underline the necessity for ongoing research. Future research should focus on enhancing real-time capabilities by developing more robust sentiment analysis systems that can effectively handle high-volume, diverse data streams across multiple platforms. Additionally, further investigation into multi-label classification techniques is needed, particularly regarding their performance across various datasets, with an emphasis on establishing standardized benchmarks for broader applicability. Improving the interpretability of complex models is essential, and future studies could explore novel frameworks for emotion visualization that are user-friendly and reliable. Moreover, examining the transferability of sentiment analysis techniques across different domains can provide insights into their adaptability and effectiveness, potentially leading to the development of models that are less reliant on specific datasets. Finally, incorporating explainable AI techniques into sentiment analysis models can enhance user trust and understanding of model predictions, thereby improving the overall user experience. By focusing on these areas, future research can contribute to refining sentiment analysis methodologies, ultimately leading to more accurate and actionable insights in e-commerce and beyond.

Acknowledgements

The authors thank Professor Dave Rushit for providing valuable guidance, insightful feedback, and continuous support throughout the development of this research on sentiment analysis techniques.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

References

[1] Pang, B. and Lee, L. (2008) Opinion Mining and Sentiment Analysis. *Foundations and Trends® in Information Retrieval*, **2**, 1-135. https://doi.org/10.1561/1500000011

[2] Liu, B. (2022) Sentiment Analysis and Opinion Mining. Morgan & Claypool Publishers.

[3] Wankhade, M., Rao, A.C.S. and Kulkarni, C. (2022) A Survey on Sentiment Analysis Methods, Applications, and Challenges. *Artificial Intelligence Review*, **55**, 5731-5780. https://doi.org/10.1007/s10462-022-10144-1

[4] Sharma, N.A., Ali, A.B.M.S. and Kabir, M.A. (2025) A Review of Sentiment Analysis:

Tasks, Applications, and Deep Learning Techniques. *International Journal of Data Science and Analytics*, **19**, 351-388. https://doi.org/10.1007/s41060-024-00594-x

[5] Ahmad, M., Aftab, S., Ali, I. and Hameed, N. (2017) Hybrid Tools and Techniques for Sentiment Analysis: A Review. *International Journal of Multidisciplinary Sciences and Engineering*, **8**, 28-33.

[6] Yue, L., Chen, W., Li, X., Zuo, W. and Yin, M. (2019) A Survey of Sentiment Analysis in Social Media. *Knowledge and Information Systems*, **60**, 617-663. https://doi.org/10.1007/s10115-018-1236-4

[7] Suryawanshi, N.S. (2024) Sentiment Analysis with Machine Learning and Deep Learning: A Survey of Techniques and Applications. *International Journal of Science and Research Archive*, **12**, 5-15. https://doi.org/10.30574/ijsra.2024.12.2.1205

[8] Devlin, J., Chang, M.-W., Lee, K. and Toutanova, K. (2019) BERT: Pre-Training of Deep Bidirectional Transformers for Language Understanding. *Proceedings of NAACL-HLT* 2019, Minneapolis, 2-7 June 2019, 4171-4186.

[9] Socher, R., Perelygin, A., Wu, J., Chuang, J., Manning, C.D., Ng, A., *et al.* (2013) Recursive Deep Models for Semantic Compositionality over a Sentiment Treebank. *Proceedings of the* 2013 *Conference on Empirical Methods in Natural Language Processing*, Seattle, 18-21 October 2013, 1631-1642. https://doi.org/10.18653/v1/d13-1170

[10] Feldman, R. (2013) Techniques and Applications for Sentiment Analysis: The Main Applications and Challenges of One of the Hottest Research Areas in Computer Science. *Communications of the ACM*, **56**, 82-89. https://doi.org/10.1145/2436256.2436274

[11] Shathik, A. and Prasad, K. (2020) A Literature Review on Application of Sentiment Analysis Using Machine Learning Techniques. *International Journal of Applied Engineering and Management Letters* (*IJAEML*): *A Refereed International Journal of Srinivas University*, **4**, 2581-7000.

[12] Chaturvedi, S., Mishra, V. and Mishra, N. (2017) Sentiment Analysis Using Machine Learning for Business Intelligence. 2017 IEEE *International Conference on Power*, *Control*, *Signals and Instrumentation Engineering* (*ICPCSI*), Chennai, 21-22 September 2017, 2162-2166. https://doi.org/10.1109/icpcsi.2017.8392100

[13] Huang, H., Zavareh, A.A. and Mustafa, M.B. (2023) Sentiment Analysis in E-Commerce Platforms: A Review of Current Techniques and Future Directions. *IEEE Access*, **11**, 90367-90382. https://doi.org/10.1109/access.2023.3307308

[14] Alonso, M.A., Vilares, D., Gómez-Rodríguez, C. and Vilares, J. (2021) Sentiment Analysis for Fake News Detection. *Electronics*, **10**, Article 1348. https://doi.org/10.3390/electronics10111348

[15] Kawade, D.R. and Oza, D.K.S. (2017) Sentiment Analysis: Machine Learning Approach. *International Journal of Engineering and Technology*, **9**, 2183-2186. https://doi.org/10.21817/ijet/2017/v9i3/1709030151

[16] Yi, S. and Liu, X. (2020) Machine Learning Based Customer Sentiment Analysis for Recommending Shoppers, Shops Based on Customers' Review. *Complex & Intelligent Systems*, **6**, 621-634. https://doi.org/10.1007/s40747-020-00155-2

[17] Deniz, E., Erbay, H. and Coşar, M. (2022) Multi-Label Classification of E-Commerce Customer Reviews via Machine Learning. *Axioms*, **11**, Article 436. https://doi.org/10.3390/axioms11090436

[18] Saura, J.R., Palos-Sanchez, P. and Grilo, A. (2019) Detecting Indicators for Startup Business Success: Sentiment Analysis Using Text Data Mining. *Sustainability*, **11**, Article 917. https://doi.org/10.3390/su11030917

[19] Alnasrawi, A.M., Alzubaidi, A.M.N. and Al-Moadhen, A.A. (2024) Improving Sentiment Analysis Using Text Network Features within Different Machine Learning Algorithms. *Bulletin of Electrical Engineering and Informatics*, **13**, 405-412. https://doi.org/10.11591/eei.v13i1.5576

[20] Mehta, K. and Panda, S.P. (2022) Sentiment Analysis on E-Commerce Apparels Using Convolutional Neural Network. *International Journal of Computing*, **21**, 234-241. https://doi.org/10.47839/ijc.21.2.2592

[21] Lin, X. (2020) Sentiment Analysis of E-Commerce Customer Reviews Based on Natural Language Processing. *Proceedings of the* 2020 2*nd International Conference on Big Data and Artificial Intelligence*, Johannesburg, 28-30 April 2020, 32-36. https://doi.org/10.1145/3436286.3436293

[22] Kundra, H., Vishnu, C., Vaishnavi, B.V., Kasireddy, C.R., Akash, G. and Jindam, S. (2024) Digital Emotions Using Sentiment Analysis for Predictive Insights on Customer Recommendations. 2024 *IEEE* 5*th India Council International Subsections Conference* (*INDISCON*), Chandigarh, 22-24 August 2024, 1-6. https://doi.org/10.1109/indiscon62179.2024.10744376

[23] Zhao, H., Liu, Z., Yao, X. and Yang, Q. (2021) A Machine Learning-Based Sentiment Analysis of Online Product Reviews with a Novel Term Weighting and Feature Selection Approach. *Information Processing & Management*, **58**, Article ID: 102656. https://doi.org/10.1016/j.ipm.2021.102656

[24] Vatambeti, R., Mantena, S.V., Kiran, K.V.D., Manohar, M. and Manjunath, C. (2024) Twitter Sentiment Analysis on Online Food Services Based on Elephant Herd Optimization with Hybrid Deep Learning Technique. *Cluster Computing*, **27**, 655-671. https://doi.org/10.1007/s10586-023-03970-7

[25] Behera, R.K., Jena, M., Rath, S.K. and Misra, S. (2021) Co-LSTM: Convolutional LSTM Model for Sentiment Analysis in Social Big Data. *Information Processing & Management*, **58**, Article ID: 102435. https://doi.org/10.1016/j.ipm.2020.102435

[26] Ray, P. and Chakrabarti, A. (2020) A Mixed Approach of Deep Learning Method and Rule-Based Method to Improve Aspect Level Sentiment Analysis. *Applied Computing and Informatics*, **18**, 163-178. https://doi.org/10.1016/j.aci.2019.02.002

[27] Jain, P.K., Saravanan, V. and Pamula, R. (2021) A Hybrid CNN-LSTM: A Deep Learning Approach for Consumer Sentiment Analysis Using Qualitative User-Generated Contents. *ACM Transactions on Asian and Low-Resource Language Information Processing*, **20**, 1-15. https://doi.org/10.1145/3457206

[28] Priyadarshini, I. and Cotton, C. (2021) A Novel LSTM-CNN-Grid Search-Based Deep Neural Network for Sentiment Analysis. *The Journal of Supercomputing*, **77**, 13911-13932. https://doi.org/10.1007/s11227-021-03838-w

[29] Jabbar, J., Urooj, I., JunSheng, W. and Azeem, N. (2019) Real-Time Sentiment Analysis on E-Commerce Application. 2019 *IEEE* 16*th International Conference on Networking*, *Sensing and Control* (*ICNSC*), Banff, 9-11 May 2019, 391-396. https://doi.org/10.1109/icnsc.2019.8743331

[30] Li, Y., Chan, J., Peko, G. and Sundaram, D. (2024) An Explanation Framework and Method for AI-Based Text Emotion Analysis and Visualisation. *Decision Support Systems*, **178**, Article ID: 114121. https://doi.org/10.1016/j.dss.2023.114121