The Scientific Temper (2025) Vol. 16 (spl-1): 63-69

E-ISSN: 2231-6396, ISSN: 0976-8653

Doi: 10.58414/SCIENTIFICTEMPER.2025.16.spl-1.09

https://scientifictemper.com/

ORIGINAL RESEARCH PAPER

Advancements in sentiment analysis – A comprehensive review of recent techniques and challenges

Mansi Harjivan Chauhan[1*], Divyang D. Vyas[2]

Abstract

In an increasingly digital world, opinions and emotions expressed across a variety of online platforms, when analyzed,propose immense potential for businesses, governments, and organizations. Sentiment analysis includes a collection of techniques that provide a fast and efficient way to classify user comments and derive meaningful information. Though sentiment analysis has been in practice for quite some time, there is a significant advancement in terms of approaches used because of increasing amounts of available data in various forms, including text, requirement of contextual understanding, business needs, etc. This article provides a comprehensive review of the latest advancements in sentiment classification in terms of scope, techniques and challenges. This literature review presents a good insight into the classification of various approaches in sentiment analysis and comparative analysis of different techniques. It also highlights the challenges in terms of the research gap and proposes future directions.

Keywords: Sentiment analysis, Machine learning, Deep learning, Aspect analysis, Emotion Detection, Fine-grained sentiment analysis

Introduction

In the current age of the internet and social media, people are drawn in by various reasons like information, news, entertainment, networking, shopping, gossip, and many more. Additionally, engaged users are accustomed to expressing their thoughts on nearly every topic. User comments on websites, social media, and other online platforms generate enormous amounts of data every day. Businesses, governments, and organizations can benefit greatly from an understanding of user attitudes and feelings through the analysis of this data, which reflects user experience, opinions, and comments.

Sentiment classification (SA) is a crucial tool for automatically comprehending and interpreting these feelings and opinions. The main function of SA, also known as opinion analysis or opinion mining, is to process natural language. Initially, SA was mainly a rule-based approach and lexicon that concentrated on determining the polarity of opinions and categorizing them as neutral, positive, or negative. (Arbane, M., Benlamri, R., Brik, Y., & Alahmar, A. D., 2023) However, the field of SA has advanced toward more reliable and accurate approaches, the majority of which are based on machine learning techniques and their further advancements like deep learning, due to the exponential growth in the availability of text data, its contextual dependencies, and the nuances of human languages. More advanced applications of SA include emotion identification, aspect-based SA, sentiment intensity estimate, and polarity detection, among others.

This paper presents a comprehensive review of recent trends in SA mainly related to the improving scope of SA and finer analysis techniques based on which the challenges, research gaps and future directions are discussed. In Section 2, various scopes of SA towards find-grained SA, aspect-based sentiment analysis, emotion analysis and intent analysis are discussed. (Bengesi, S., Oladunni, T., Olusegun, R., & Audu, H., 2023). In Section 3 evolution of SA approaches is critically reviewed, covering lexicon-based, conventional machine learning-based, deep-learning and hybrid approaches. This is followed by identification of challenges and research gaps for SA in Section 4 and suggestions on future directions in Section 5 last Section 6 with Conclusion.

[1]Computer Engineering, Atmiya University, Rajkot, India.

[2]Electronics & Communication Engineering, Atmiya University, Rajkot, India.

***Corresponding Author:** Mansi Harjivan Chauhan, Computer Engineering, Atmiya University, Rajkot, India., E-Mail: mansih1998@gmail.com

How to cite this article: Chauhan, M.H., Vyas, D.D. (2025). Advancements in sentiment analysis – A comprehensive review of recent techniques and challenges. The Scientific Temper, **16**(spl-1):63-69.

Doi: 10.58414/SCIENTIFICTEMPER.2025.16.spl-1.09

Source of support: Nil

Conflict of interest: None.

Received: 10/04/2025 **Accepted:** 08/05/2025 **Published** : 21/05/2025

Nuance Scopes in Sentiment Analysis

Nuance scopes in sentiment analysis enable analysis at different levels based on the requirement. Document-level sentiment analysis evaluates the overall sentiment of an entire text, while sentence-level analysis breaks it down further for more precision. Aspect-based sentiment analysis (ABSA) goes even deeper by identifying sentiments related to specific features or topics within a text. (Gogula, S. D., Rahouti, M., Gogula, S. K., Jalamuri, A., & Jagatheesaperumal, S. K., 2023). Additionally, emotion detection and intensity measurement help capture subtle emotional expressions, making sentiment analysis more effective in understanding user intent and engagement.

In real-world applications, sentiment analysis is widely used in customer feedback analysis to assess product evaluations, remarks on digital networking, and survey responses. Businesses use it to understand consumer sentiment, improve customer experience, and enhance products or services. Social media monitoring is another crucial application where companies track brand perception and detect potential PR crises by analyzing posts, comments, and discussions. Political organizations and government agencies also use sentiment analysis to gauge public opinion on policies and election trends.

Beyond business and marketing, sentiment analysis significantly contributes to healthcare and finance. In mental health applications, AI-driven platforms analyze patient conversations to detect signs of emotional distress, anxiety, or depression. In the financial sector, sentiment analysis helps predict market trends by assessing news articles, investor sentiment, and economic reports. (Revathi, K. L., Satish, A. R., & Rao, P. S., 2023, April). By providing valuable insights, sentiment analysis supports informed decision-making and proactive responses in various industries.

With advancements in NLP and machine learning, sentiment analysis continues to improve in accuracy and efficiency. Transformer-based models like BERT and RoBERT enhance contextual understanding, while rule-based tools like VADER help process informal text, including slang and emojis. The integration of multiple sentiment analysis approaches allows for deeper, more accurate sentiment interpretation. Consequently, emotion recognition has emerged as an essential tool for businesses, researchers, and policymakers in understanding human emotions and making data-driven decisions.

Sentiment Analysis Techniques

Sentiment classification has changed significantly in recent years, moving from simple rule-based methods and lexicon to complex deep learning models. For simplicity and interpretability, lexicon-based approaches first linked words to particular moods using established dictionaries. Nevertheless, these methods frequently encountered difficulties in interpreting context-dependent meanings and the subtleties of human language, including sarcasm and idioms.

Sentiment analysis approaches are becoming more dynamic as machine learning technology evolves. By recognizing patterns in the data, supervised learning models trained on labeled datasets began to classify sentiment. (Jassim, M. A., Abd, D. H., & Omri, M. N., 2023) Compared to lexicon-based techniques, algorithms like logistic regression and support vector machines (SVMs) improved accuracy by taking into account the context in which words appeared. Nonetheless, these models were unable to accurately capture the complex language patterns and distant linkages observed in the text.

Deep learning managed to bring about some kind of revolutionary shift in sentiment analysis. Neural networks, particularly LSTM and CNNs, have great promise in modeling complex data patterns. CNNs were excellent at detecting local characteristics and patterns, whereas LSTMs were good at capturing sequential dependencies, making them suitable for understanding sentiment flow in the text. These models outperformed traditional machine learning techniques, especially when dealing with large and complex datasets. For example, a comparison study found that deep learning models outperformed conventional methods in opinion tasked with the responsibility.

Transformer-based models, such as Bidirectional Encoder Representations from Transformers (BERT), helped to accelerate the field even more. Because BERT is bidirectional, it can determine a phrase's frame of reference by looking at the sentences around it, allowing it to better understand linguistic nuances. (Sofiya, W., & Setiawan, E. B., 2023). Research has shown that BERT outperforms previous models in sentiment classification tasks by managing context-dependent sentiments more effectively and accurately. For example, studies comparing BERT to lexicon-based approaches found that this one significantly improved sentiment classification across a variety of datasets.

Despite significant advances made by neural network models, lexicon-based approaches remain useful, particularly in situations requiring interpretability and less processing power. Recent research has focused on agile methodologies that integrate the perseverance of deep neural networks with the visibility of linguistic methods. For example, proposed to combine explainable lexicons and transformer models to enhance sentiment classification performance and lexicon visibility while maintaining interpretability.

Sentiment analysis has evolved for a long time, from simple linguistic techniques to complex deep neural networks, with each phase acknowledging the deficiencies of the earlier one. To better understand and analyze human moods in text, the current trend would be towards optimization methods that find a middle ground between generalization ability and accuracy, combining the benefits of both traditional and contemporary approaches.

Related Literature

Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

(Huang, H., Asemi, A., & Mustafa, M. B., 2023) Conducted a comprehensive analysis of machine learning and deep learning methodologies employed for sentiment analysis within contemporary e-commerce platforms. Support Vector Machines (SVM) and Naïve Bayes (NB) were found to consistently outperform other classifiers among machine learning approaches. Conversely, Recurrent Neural Networks (RNN) showed better performance in deep learning scenarios. Three main methods for sentiment Classification were investigated by (Huang, H., Asemi, A., & Mustafa, M. B., 2023): lexicon-based, machine learning-based, and a hybridized model that combined the two approaches. Their results demonstrated that hybridization greatly improves sentiment categorization results in terms of both accuracy and quality.

(Soumya, S., & Pramod, K. V., 2021) Conducted sentiment classification on the Malayalam Tweets dataset using a lexicon-based methodology in conjunction with SVM and Random Forest (RF) classifiers. Their findings showed that SVM and RF classifiers produced impressive accuracies of 92.9 and 93.4%, respectively, while the lexicon-based approach acquired an accuracy of 84.8%. A recommendation system specifically designed for the sentiment classification of hotel evaluations was created by (Ray, B., Garain, A., & Sarkar, R., 2021). They classified factors including cleanliness, service, location, cost, accommodation, cuisine, amenities, and personnel using aspect-based sentiment analysis. When applied to classification, the BERT algorithm achieved a higher accuracy rate of 92.36% than the LSTM and RNN models.

Djoko *et al*. evaluated reviews from a COVID-19 data source with labels that had been individually adapted into five sentiment categories—fear, anger, sadness, love, and happiness—using a Naïve Bayes classifier. Their model's accuracy was 85.4%. Similar to this, Gagandeep *et al*. used an LSTM-based deep learning model to classify sentiment across three datasets: Sentiment140, SemEval-2014, and STS-Gold. They demonstrated good accuracy ratings of 90, 90.02, and 92.7%, respectively. To explore and classify airline evaluations using text, Aksh Patel *et al*. used BERT and evaluated its comparative accuracy. According to their findings, BERT (83%) performed better than more conventional classifiers like Adaboost (72%), random forest (77%), K-nearest neighbors (67%), SVM (65%), decision tree (67%), and logistic regression (65%).

Staphord *et al*. assessed sentiment on a Monkeypox dataset from Twitter using various machine-learning strategies., including KNN, SVM, RF, LR, NB, Multilayer Perceptron, and XGBoost. According to experimental results, SVM achieved the greatest accuracy of 93.48%. Using supervised machine learning algorithms, Harjasdeep Singh *et al*. concentrated on sentiment classification using Twitter movie reviews. Their analysis revealed that the effectiveness of K-Nearest Neighbours (71.3%), SVM (87.5%), Naïve Bayes (84.5%), and Decision Trees (71.1%) varied, with SVM producing the greatest results. Say Hong Lye *et al*. used the IMDB movie opinion assessment database. To investigate sentiment analysis for consumer intent prediction, and the RF system produced an impressive 77.3% accuracy rate.

Rim Nasfi *et al*. A hybrid sentiment classification model was developed by combining Hidden Markov Models (HMM) and SVM. Their model obtained accuracy rates of 86.4% and 88.94% on the Amazon and IMDB datasets, correspondingly. Devi *et al*. extended the capabilities of sentiment classification by developing a blend of deep learning models that incorporates both CNN and LSTM architectures. Their approach was evaluated and equated with other models, including SVM, CNN, ANN, and LSTM, across 11 different datasets and achieved a maximum accuracy of 96%. Researchers Ulligaddala *et al*. developed a hybrid classifier combining support vector machine (SVM) and k-nearest neighbor (KNN) techniques, resulting in an accuracy rate of 99.82% on a dataset of SMS messages. A comparative study was carried out by Endah *et al*. to a performance assessment has been completed on four supervised machine learning models on an Indonesian memes' dataset. Those findings demonstrated that SVM achieved 62.8%, NB reached 65.4%, decision tree scored 63.8%, and CNN obtained 60.8% efficacy.

Challenges and Research Gaps

Challenges in Sentiment Analysis

Despite advancements in sentiment analysis techniques, various challenges persist that hinder about accurateness and productivity of existing models. The key challenges are:

Navigating Sarcasm, Irony, and Ambiguity

Sentiment analysis continues to be hampered by the presence of sarcasm, irony, and subtle sentiment expressions. Machine learning models and traditional lexicons often struggle to accurately identify when sentiment is expressed in a figurative or non-literal sense, as seen in phrases such as "Great!" The flight has been delayed again. Sarcasm detection relies heavily on the availability of substantial annotated datasets, Tragically, these sets of data are not currently accessible this time in short supply.

Contextual and Aspect-Based Sentiment Analysis

Fine-grained opinion analysis relies heavily on Aspect-based Sentiment Analysis (ABSA), yet current models frequently struggle to differentiate sentiment at various levels, as seen

Table 1: Comparison of literature

S. No.	*Methods used*	*Key findings & accuracy*
1	SVM, Naïve Bayes (NB), Recurrent Neural Network (RNN)	SVM & NB consistently outperformed other ML models; RNN demonstrated superior accuracy among deep learning methods. Machine learning models SVM and NB consistently outperformed the competition others, while RNN showed higher accuracy in comparison to various other methods of deep learning.
2	Lexicon-based, Machine Learning, Hybrid approach	The hybridization of lexicon-based and ML techniques significantly improved sentiment classification accuracy. Combining lexicon-based and machine learning techniques resulted in a substantial enhancement of sentiment classification accuracy.
3	Lexicon-based, Support Vector Machine (SVM), Random Forest (RF)	Lexicon-based: 84.8%; SVM: 92.9%; RF: 93.4% (Best Performance).
4	BERT, Long Short-Term Memory (LSTM), RNN	BERT achieved 92.36%, outperforming LSTM and RNN on hotel review sentiment classification.
5	Naïve Bayes (NB)	NB classifier achieved 85.4% accuracy on a COVID-19 sentiment dataset labeled across five emotions.
6	Long Short-Term Memory (LSTM)	LSTM achieved 90% (STS-Gold), 90.02% (SemEval-2014), 92.7% (Sentiment140), demonstrating robust sentiment classification.
7	BERT, Logistic Regression, K-Nearest Neighbors (KNN), SVM, Decision Tree, RF, Adaboost	BERT achieved the highest accuracy (83%), followed by RF (77%), Adaboost (72%), KNN & Decision Tree (67%), SVM & LR (65%).
8	KNN, SVM, RF, Logistic Regression (LR), NB, Multilayer Perceptron (MLP), XGBoost	SVM outperformed all models, achieving 93.48% accuracy in Monkeypox sentiment analysis.
9	KNN, SVM, NB, Decision Tree	SVM: 87.5%, NB: 84.5%, KNN: 71.3%, Decision Tree: 71.1% (SVM performed best).
10	Random Forest (RF)	RF achieved 77.3% accuracy on IMDB movie opinion assessment database for sentiment classification.
11	Hidden Markov Model (HMM), Support Vector Machine (SVM)	Hybrid HMM-SVM model achieved 86.4% (Amazon) and 88.94% (IMDB), outperforming standalone models.
12	Convolutional Neural Network (CNN), LSTM (Hybrid)	Hybrid CNN-LSTM achieved 96%, outperforming standalone SVM, CNN, ANN, and LSTM models.
13	Hybrid SVM and KNN	The proposed hybrid model attained an impressive 99.82% accuracy on the SMS messages dataset.
14	SVM, NB, Decision Tree, CNN	Performance comparison: NB (65.4%), Decision Tree (63.8%), SVM (62.8%), CNN (60.8%).

in statements such as "The hotel service was excellent, but the food was terrible." Continuing to develop context-aware models with the aid of sophisticated transformers and attention mechanisms presents a persistent challenge.

Language Processing for Multilingual and Code-Mixed Texts

The majority of sentiment analysis studies centre on English-language datasets, whereas data from real-world applications frequently comprises multiple languages or a combination of languages (e.g., "This movie is amazing, लेकिन थोड़ा लंबा था" - an example of a Hindi-English mix). Current models are unable to accurately determine sentiment in mixed-language texts, necessitating improvements in multilingual NLP models.

Domain-Specific Adaptability

Models trained on a specific domain, such as movie reviews, frequently struggle to achieve good results in a different domain, like financial news. Generalization across different domains is a challenge for a single model, as sentiment can be context-dependent.

The transparency and understandability of artificial intelligence systems

Sentiment classifiers developed with deep learning models, like BERT and LSTM, achieve high levels of accuracy, but they often lack interpretability. In high-risk sectors such as finance and healthcare, organizations necessitate explainable AI (XAI) methods to comprehend the reasoning behind sentiment forecast determinations.

Real-time data handling and high scalability capabilities

Real-time sentiment classification is necessary for various real-world applications, including social media monitoring and analyzing customer feedback. The fact that deep learning models require a significant amount of processing

power presents a hurdle in scaling them to accommodate high-velocity data streams.

Challenges of Unbalanced Data and Annotation Problems

Most sentiment datasets are plagued by class imbalances, with neutral or positive sentiments holding a disproportionate majority. Labeling large datasets manually is a labor-intensive and costly process, resulting in inconsistent annotations that subsequently affect model performance.

Research Gaps in Sentiment Analysis

Although recent research has made great strides, there are still several areas that need more study.to existing research gaps.

Limited Applicability across Various Domains

Most sentiment analysis models excel within a particular dataset but struggle to apply their insights across diverse domains as a result of differences in language usage and the way sentiment is expressed. Future research should investigate the use of transfer learning and domain adaptation techniques to enhance model generalizability.

Limited multilingual capabilities and lack of support for low-resource languages

Research on sentiment analysis in languages with limited resources and in datasets that support multiple languages is scarce. Further investigation is required in cross-lingual sentiment analysis employing models such as BERT, XLM-R, and a few-shot learning approach.

Deficiencies in Hybrid Model Development

Research has shown that hybrid models, which integrate lexicon-based approaches and deep learning, are highly effective, but a universally accepted method for combining these techniques does not exist. Enhancing accuracy across datasets will require future work to focus on dynamic and adaptive hybrid frameworks.

Enhancing the efficacy of Aspect-Based and Emotion Detection Models

Many sentiment analysis models primarily concentrate on the overall sentiment orientation, whereas real-world applications necessitate the classification of specific aspects and subtleties of emotions. Investigating more sophisticated transformer-based architectures may lead to enhanced contextual sentiment analysis capabilities.

AI Sentiment Analysis with Explainable Features

Despite their excellent accuracy, deep learning models are opaque. Techniques for explainable AI (XAI) that make sentiment forecasts comprehensible and transparent are needed, particularly for applications in the legal, medical, and financial fields.

Real-time sentiment processing and expansion

Because of computational limitations, current models are not optimized for real-time applications. To process high-velocity sentiment data streams with little resource usage, research is required to create lightweight, effective architectures.

Incorporating AI with Other Applications

The majority of sentiment analysis research focuses only on classification, not incorporating it into more general AI uses like chatbots, recommender systems, social media trend monitoring, and fake news identification. Subsequent investigations want to examine multi-task learning strategies that integrate sentiment an

Future directions

Research into sentiment analysis should be directed towards the creation of sophisticated context-aware and aspect-based models based on transformer architectures such as BERT and RoBERT to refine sarcasm, irony, and emotion detection through the use of multimodal learning and expanding multilingual and code-mixed sentiment analysis capabilities with cross-lingual techniques such as BERT and zero-shot learning. The integration of hybrid and ensemble models can enhance performance, and the use of explainable AI techniques such as SHAP and LIME will increase interpretability. Real-time sentiment analysis necessitates the use of lightweight, scalable architectures that can process high-velocity data streams in a highly efficient manner. Exploring domain adaptation and transfer learning techniques can enhance cross-domain sentiment analysis capabilities. Sentiment analysis should be incorporated into more extensive AI applications such as recommender systems, chatbot interactions, and fake news detection, with consideration given to ethical issues and bias reduction through fairness-aware learning and adversarial training methods. These developments will drive the beginning of more robust, scalable, and interpretable sentiment analysis models For a variety of real-world applications.

Conclusion

Submissions should always include the following sections: an abstract, an introduction, a conclusion and a references section. If any of the above sections are not included, the paper will be unsubmitted, and you will be asked to add the relevant section. Sentiment analysis has progressed from basic word-based techniques to complex neural network methods, tackling numerous difficulties, including contextual comprehension, aspect-based sentiment identification, and multilingual processing. Significant improvements in sentiment classification accuracy have been achieved through advancements such as transformer models, yet difficulties remain in addressing sarcasm, adapting across domains, providing explanations, and ensuring real-time scalability. Further progress in sentiment analysis will depend on the integration of hybrid models,

explainable AI methodologies, and real-time processing technologies. As sentiment analysis evolves and gains wider adoption across various sectors, future research should concentrate on enhancing its interpretability, refining its ability to comprehend context-dependent sentiment, and improving its compatibility with more extensive AI-driven systems.

Acknowledgment

We would like to sincerely thank the authors of the research and publications that this article has evaluated. This review has been greatly influenced by their innovative research and valuable contributions to the area. This review would not be considered possible without the research they conducted.

Conflict of Interest

The authors declare that there are no conflicts of interest regarding the publication of this review.

References

Arbane, M., Benlamri, R., Brik, Y., & Alahmar, A. D. (2023). Social media-based COVID-19 sentiment classification model using Bi-LSTM. *Expert Systems with Applications*, *212*, 118710.

Asmawati, E., Saikhu, A., & Siahaan, D. (2022, October). Sentiment analysis of text memes: A comparison among supervised machine learning methods. In 2022 9th International Conference on Electrical Engineering, Computer Science and Informatics (EECSI) (pp. 349-354). IEEE.

Atzeni, M., Dridi, A., & Reforgiato Recupero, D. (2017). Fine-grained sentiment analysis on financial microblogs and news headlines. In *Semantic web evaluation challenge* (pp. 124-128). Cham: Springer International Publishing.

Bengesi, S., Oladunni, T., Olusegun, R., & Audu, H. (2023). A machine learning-sentiment analysis on Monkeypox outbreak: An extensive dataset to show the polarity of public opinion from twitter tweets. *IEEE Access*, 11, 11811-11826.

Dragoni, M., & Reforgiato Recupero, D. (2016). Challenge on fine-grained sentiment analysis within ESWC2016. In *Semantic Web Challenges: Third SemWebEval Challenge at ESWC 2016, Heraklion, Crete, Greece, May 29-June 2, 2016, Revised Selected Papers 3* (pp. 79-94). Springer International Publishing.

Dridi, A., Atzeni, M., &Reforgiato Recupero, D. (2019). FineNews: fine-grained semantic sentiment analysis on financial microblogs and news. *International Journal of Machine Learning and Cybernetics*, 10, 2199-2207.

Gogula, S. D., Rahouti, M., Gogula, S. K., Jalamuri, A., & Jagatheesaperumal, S. K. (2023). An Emotion-Based Rating System for Books Using Sentiment Analysis and Machine Learning in the Cloud. *Applied Sciences*, 13(2), 773.

Guo, X., Yu, W., & Wang, X. (2021). An overview on fine-grained text sentiment analysis: Survey and challenges. *In Journal of Physics: Conference Series* (Vol. 1757, No. 1, p. 012038). IOP Publishing.

Guzman, E., & Maalej, W. (2014, August). How do users like this feature? a fine grained sentiment analysis of app reviews. *In 2014 IEEE 22nd international requirements engineering conference (RE)* (pp. 153-162). Ieee.

https://medium.com/analytics-vidhya/sentiment-analysis-building-from-the-ground-up-e12e9195fac4

https://www.snowflake.com/guides/understanding-customer-sentimentanalysis/#:~:text=-Intent%2Dbased%20sentiment%20analysis,intention%20behind%20a%20user's%20statement.

Huang, H., Asemi, A., & Mustafa, M. B. (2023). Sentiment Analysis in E-commerce Platforms: A Review of Current Techniques and Future Directions. *IEEE Access*.

Jassim, M. A., Abd, D. H., & Omri, M. N. (2023). A survey of sentiment analysis from film critics based on machine learning, lexicon and hybridization. *Neural Computing and Applications*, 35(13), 9437-9461.

Kaur, G., & Sharma, A. (2023). A deep learning-based model using hybrid feature extraction approach for consumer sentiment analysis. *Journal of Big Data*, 10(1), 5.

Kausar, S., Huahu, X. U., Ahmad, W., & Shabir, M. Y. (2019). A sentiment polarity categorization technique for online product reviews. *IEEE Access*, 8, 3594-3605.

Luo, J., Huang, S., & Wang, R. (2021). A fine-grained sentiment analysis of online guest reviews of economy hotels in China. *Journal of Hospitality Marketing & Management*, 30(1), 71-95.

Lye, S. H., & Teh, P. L. (2021, September). Customer intent prediction using sentiment analysis techniques. In 2021 11th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications (*IDAACS*) (Vol. 1, pp. 185-190). IEEE.

Mercha, E. M., & Benbrahim, H. (2023). Machine learning and deep learning for sentiment analysis across languages: A survey. Neurocomputing, 531, 195-216.

Munikar, M., Shakya, S., & Shrestha, A. (2019, November). Fine-grained sentiment classification using BERT. *In 2019 Artificial Intelligence for Transforming Business and Society (AITB)* (Vol. 1, pp. 1-5). IEEE.

Nasfi, R., & Bouguila, N. (2022, August). Sentiment analysis from user reviews using a hybrid generative-discriminative HMM-SVM approach. In *Joint IAPR International Workshops on Statistical Techniques in Pattern Recognition (SPR) and Structural and Syntactic Pattern Recognition (SSPR)* (pp. 74-83). Cham: Springer International Publishing.

Patel, A., Oza, P., & Agrawal, S. (2023). Sentiment Analysis of Customer Feedback and Reviews for Airline Services using Language Representation Model. *Procedia Computer Science*, 218, 2459-2467.

Rahman, A., Sadat, M., & Siddik, S. (2021). Sentiment analysis on Twitter data: comparative study on different approaches. *International Journal of Intelligent Systems and Applications*, 13(4), 1.

Ray, B., Garain, A., & Sarkar, R. (2021). An ensemble-based hotel recommender system using sentiment analysis and aspect categorization of hotel reviews. *Applied Soft Computing*, 98, 106935.

Revathi, K. L., Satish, A. R., & Rao, P. S. (2023, April). Feature level Fine Grained Sentiment Analysis for Classifying Online Restaurant Reviews. *In 2023 Second International Conference on Electrical, Electronics, Information and Communication Technologies (ICEEICT)* (pp. 1-5). IEEE.

Saha, U., Mahmud, M. S., Chakrobortty, A., Akter, M. T., Islam, M. R., & Al Marouf, A. (2022, April). Sentiment Classification in Bengali News Comments using a hybrid approach with Glove. *In 2022 6th International Conference on Trends in Electronics and Informatics (ICOEI)* (pp. 01-08). IEEE.

Singh, H., & Srivastava, D. (2023, January). Sentiment Analysis: Quantitative Evaluation of Machine Learning Algorithms. *In 2023 5th International Conference on Smart Systems and Inventive Technology (ICSSIT)* (pp. 946-951). IEEE

Sofiya, W., & Setiawan, E. B. (2023). FINE-GRAINED SENTIMENT ANALYSIS IN SOCIAL MEDIA USING GATED RECURRENT UNIT WITH SUPPORT VECTOR MACHINE. *Jurnal Teknik Informatika (Jutif),* 4(3), 511-519.

Soumya, S., & Pramod, K. V. (2021, January). Fine grained sentiment analysis of Malayalam tweets using lexicon based and machine learning based approaches. *In 2021 4th Biennial International Conference on Nascent Technologies in Engineering (ICNTE)* (pp. 1-6). IEEE.

Soumya, S., & Pramod, K. V. (2021, January). Fine grained sentiment analysis of Malayalam tweets using lexicon based and machine learning based approaches. *In 2021 4th Biennial International Conference on Nascent Technologies in Engineering (ICNTE)* (pp. 1-6). IEEE.

Srinivasarao, U., & Sharaff, A. (2023). Machine intelligence-based hybrid classifier for spam detection and sentiment analysis of SMS messages. Multimedia Tools and Applications, 1-31.

Tang, F., Fu, L., Yao, B., & Xu, W. (2019). Aspect based fine-grained sentiment analysis for online reviews. *Information Sciences*, 488, 190-204.

Tang, Y., & Zhang, H. (2022, September). Fine-Grained Sentiment Analysis of Online-Offline Danmaku Based on CNN and Attention. *In CCF Conference on Computer Supported Cooperative Work and Social Computing* (pp. 194-206). Singapore: Springer Nature Singapore.

Wan, Y., Nie, H., Lan, T., & Wang, Z. (2015, August). Fine-grained sentiment analysis of online reviews. *In 2015 12th International Conference on Fuzzy Systems and Knowledge Discovery (FSKD)* (pp. 1406-1411). IEEE.

Wang, Y., Huang, G., Li, M., Li, Y., Zhang, X., & Li, H. (2023). Automatically Constructing a Fine-Grained Sentiment Lexicon for Sentiment Analysis. *Cognitive Computation*, 15(1), 254-271.

Wang, Z., Chong, C. S., Lan, L., Yang, Y., Ho, S. B., & Tong, J. C. (2016, December). Fine-grained sentiment analysis of social media with emotion sensing. *In 2016 Future technologies conference (FTC)* (pp. 1361-1364). IEEE.

Widodo, D. A., Iksan, N., & Sunarko, B. (2023). Sentiment Analysis of Twitter Media for Public Reaction Identification on Covid-19 Monitoring System using Hybrid Feature Extraction Method. *International Journal of Intelligent Systems and Applications in Engineering,* 11(1), 92-99.

Xiao, Y., Li, C., Thürer, M., Liu, Y., & Qu, T. (2022). User preference mining based on fine-grained sentiment analysis. *Journal of Retailing and Consumer Services*, 68, 103013.

Yang, L., Yu, J., Zhang, C., & Na, J. C. (2021). Fine-grained sentiment analysis of political tweets with entity-aware multimodal network. In *Diversity, Divergence, Dialogue: 16th International Conference, iConference 2021, Beijing, China, March 17–31, 2021, Proceedings, Part I 16* (pp. 411-420). Springer International Publishing.

Zhang, J., Zhang, A., Liu, D., & Bian, Y. (2021). Customer preferences extraction for air purifiers based on fine-grained sentiment analysis of online reviews. *Knowledge-Based Systems*, *228*, 107259.

Zhang, Y., Zhu, C., & Xie, Y. (2023). Fine-grained sentiment analysis of cross-domain Chinese e-commerce texts based on SKEP_Gram-CDNN. *IEEE Access*, *11*, 74058-74070.