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A Comprehensive Survey on Sentiment Analysis Techniques

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Abstract. Sentiment analysis is a natural language processing (NLP) technique used to decide if the underlying sentiment is positive, negative, or neutral. Subjective information from the text can be extracted using sentiment analysis by recognizing its context and position. Data from a variety of sources, like social network comments, news stories, consumer reviews, and more, can be used for sentiment analysis. Sentiment analysis uses different algorithms to analyze words, phrases, and context available in text and different procedures to determine the overall sentiment communicated. There are various ways in which sentiment analysis is performed, ranging from rule-based methods that use lists of positive and negative terms as labeled data for training machine learning algorithms to building classifiers. Understanding social sentiment, underlying intents, and responses to various characteristics of humans can be done with the help of sentiment analysis, which helps in decision-making. The primary goal of this work is to provide the audience with the knowledge needed to understand sentiment analysis, highlight potential opportunities and challenges, and investigate recent studies that have been published in reputable resources focusing on the field of sentiment analysis in NLP.

Keywords: Convolutional Neural Network (CNN); Internet Movie Database (IMDb); Machine Learning; Recurrent Neural Network (RNN); Sentiment Analysis

1. Introduction

Sentiment analysis, often known as opinion mining, looks at how individuals feel about particular things. Sentiment analysis is a subfield of computational linguistics and NLP that deals with techniques for extracting, categorizing, comprehending, and assessing the opinions expressed in online publications (Siswanto *et al.*, 2022). It is also known as opinion mining of texts (Techtarget, 2023). The advancement of sentiment analysis has been made easier by the abundance of online text data, especially when it comes to speculating on people's attitudes, opinions, and beliefs. Sentiment analysis has been widely utilized to forecast public sentiment and trends in a variety of scenarios. Academics studying political communication use sentiment analysis on social media posts to gather public opinion on

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presidential candidates and to precisely forecast election outcome.

Studies in economics show that stock market trends can be predicted by sentiment analysis of news reports, social media posts, and other sources of information (Ren, Wu, and Liu, 2018). Sentiment analysis has grown in importance as a component of natural language processing. Sentiment analysis in teaching assessment can assist teachers in precisely and promptly modifying the lesson plan to reflect students' genuine feelings about the course to raise the Caliber of instruction (Zhai *et al.*, 2020).

Online commerce is one of the economic areas in the contemporary world that is expanding the quickest. Nowadays, a lot of goods are purchased through online merchants. Reviews frequently affect online product purchases. Therefore, the importance of finding fake reviews is increasing, and the success of a system for identifying bogus reviews relies heavily on sentiment analysis (Hassan and Islam, 2021).

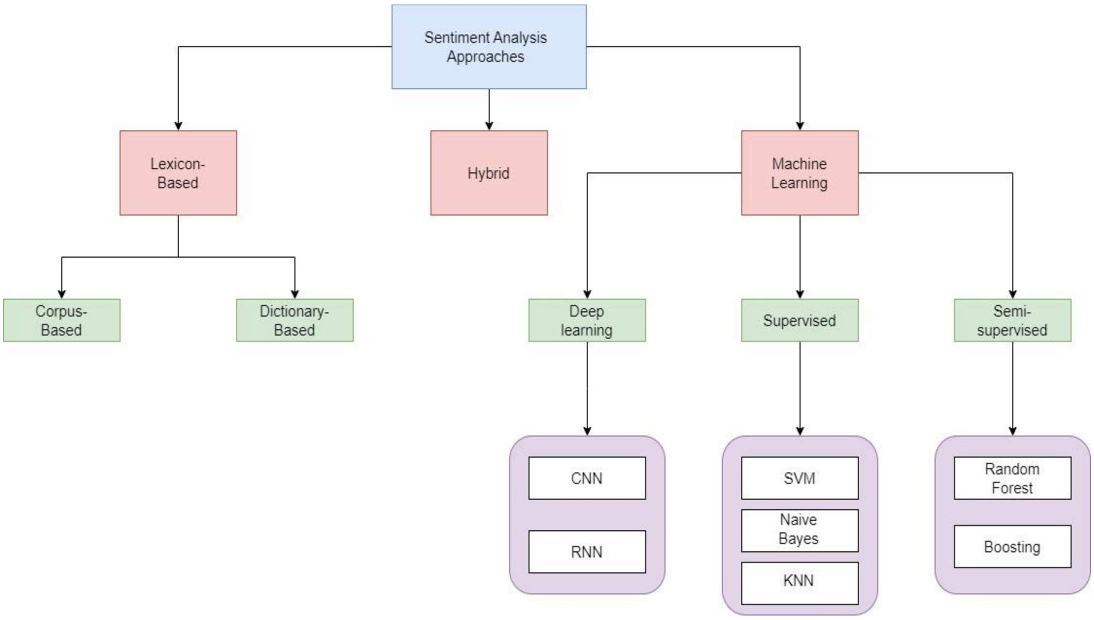

Figure 1 Sentiment Analysis Methods

Figure 1 illustrates the important approaches used for Sentiment analysis, like deep learning approaches such as CNN and RNN, which can extract complex patterns from text. We present an overview of the current state-of-the-art techniques in sentiment analysis in this survey study, including the primary methodologies, applications, datasets, evaluation criteria, and problems. We also examine current trends and future directions in the discipline, highlighting growing research topics and potential prospects. Overall, the purpose of this survey article is to give a complete and up-to-date review of the topic of sentiment analysis, which can be used by both scholars and practitioners.

2. Applications

Sentiment analysis has a wide range of applications across various fields, including:

1. Customer insights: By utilizing sentiment analysis, businesses can gain insights into their customers' attitudes, perceptions, and sentiments regarding their products, services, or brand. Making data-driven decisions to enhance their offerings and improve the customer experience can assist organizations in gaining a deeper understanding of their customers' needs, preferences, and pain points (Fairlie, 2022).

2. Brand management: It's crucial for a company to grasp the factors driving customer emotions, what aspects of its product or service succeed, and what doesn't. Machine learning, facilitated by sentiment mining techniques, empowers businesses to comprehend their customers' sentiments towards the brand and, most importantly, their expectations. Even when feedback is conveyed through videos, Repustate's sentiment analysis tool, equipped with its Video Content Analysis (VCA) feature, ensures that no vital data is missed. These data can be used by businesses to proactively neutralize negative feelings and develop a more focused branding strategy (Robinson, 2021; Trends, 2020).
3. Decision-making and strategy development: Sentiment analysis provides valuable data for decision-making and strategy development. By understanding customer sentiment and feedback, businesses can make informed decisions about product improvements, marketing strategies, customer engagement, and other business initiatives (Repustate, 2022).

3. Literature

The findings showed that various machine learning algorithms produced varying degrees of accuracy; Naive Bayes and Support Vector Machines are among the top techniques. Pretrained embeddings were employed in various studies, along with deep learning techniques like CNNs and RNNs. Deep learning models for sentiment analysis, including CNNs, RNNs, LSTMs, and GRUs, have gained popularity. Various machine learning algorithms and deep learning approaches were employed, with some models reaching great accuracy on sentiment analysis datasets such as the IMDb, Twitter US Airline Sentiment, and Sentiment140. However, there are still difficulties in effectively analyzing poorly organized and caustic words, as well as a lack of fine-grained sentiment analysis, reliance on annotated data, and potential bias in training data. The research emphasizes the shortcomings of present sentiment analysis approaches and recommends that more trustworthy language models are required to solve the obstacles provided by poorly organized and sarcastic messages (Tan, Lee, and Lim, 2023).

This scientific research examines numerous strategies for sentiment analysis in textual data, such as product and consumer evaluations, social media posts, and other types of data. It outlines two fundamental methodologies: lexicon-based techniques and machine-learning approaches. The Lexicon-Based Approach employs a sentiment lexicon, which contains information on positive and negative words and phrases. The research investigates several machine learning methods used in sentiment analysis, such as Naive Bayes, linear regression, SVM, and deep learning. The researchers believe sentiment analysis may be used to aid decision-making in numerous sectors of the economy (Appiahene *et al.*, 2022).

The research covers a thorough evaluation of the literature to find the most effective machine learning-based approaches for doing Urdu-based sentiment analysis (SA). The evaluation sought to uncover primary papers addressing machine learning-based SA concerns published in the last four years. 40 papers were chosen and evaluated using quality evaluation indicators. According to the findings, machine learning approaches, including deep learning and supervised learning, have been widely applied to Urdu-based SA. To enhance the overall performance of sentiment analysis (SA), the research suggests combining SA techniques with information retrieval, machine translation, and natural language processing (NLP) approaches (Liaqat *et al.*, 2022).

The paper provides an overview of the issues and approaches associated with sentiment analysis, often known as opinion mining, which uses NLP to extract relevant information from internet resources. This is critical for businesses and government agencies seeking accurate user feedback for future actions. They show how combining machine learning and dictionary-based techniques may improve sentiment categorization accuracy dramatically. The value of sentiment analysis in providing decision-making information is emphasized in applications of sentiment analysis within the industry and academic research. Nonetheless, several obstacles persist (Gouthamia and Hegde, 2021).

This research presents the findings of a comprehensive review of 18 research studies on sentiment analysis in NLP. For sentiment analysis, the research used machine learning algorithms, with Nave Bayes being the most used. Datasets were frequently culled from microblogs like Twitter and other internet sources. Lexicon-based approaches were also utilized to extract characteristics such as unigrams, enhanced words, and bigrams from Turkish, Arabic, and Bengali texts, with accuracies ranging from 73% (Hilario *et al*., 2021).

In this paper (Hassan and Islam, 2021), TF-IDF-based sentiment classification model was developed that can classify sentiment value with 92% accuracy. In this study (Goel and Batra, 2020), Sentiment Analysis was carried out using a deep neural network called the RNN as well as machine learning methods, and this research discovered that the RNN model performed more accurately. This study (Poornima and Priya, 2020) examined the performance of three machine learning methods: SVM, Multinomial Naive Bayes, and Logistic regression. When the Bigram model was utilized, the Logistic Regression attained an accuracy of roughly 86%.

The research presents an introduction to the difficulties and methodologies involved in sentiment analysis. The authors discuss big data sets, sentiment analysis on non-textual material, and the importance of accuracy, precision, recall, and the F-measure in assessing results. They demonstrate how combining machine learning and dictionary-based approaches may significantly enhance sentiment classification accuracy. The importance of sentiment analysis in delivering decision-making information is underlined in sentiment analysis applications in industry and academic research. Nonetheless, several challenges remain (Hamed, Ezzat, and Hefny, 2020).

This scholarly research delves into the field of sentiment analysis, also known as opinion mining, and how it can detect and categorize emotions and views conveyed in the text. The research investigates many ways of sentiment analysis, such as machine learning and lexical analysis. It emphasizes the importance of proper training sets for accurate sentiment analysis as well as linguistic components of natural language processing. The paper concludes by examining the potential applications and benefits of sentiment analysis. It examines several sentiment analysis machine learning techniques, such as Naive Bayes, Maximum Entropy, and Support Vector Machines. According to the study, SVM, Naive Bayes, and neural networks have the best accuracy and may be regarded as baseline learning techniques. However, lexicon-based strategies were also beneficial in other cases. The study emphasizes the significance of gathering large volumes of data for sentiment analysis to provide appropriate findings (Mehta and Pandya, 2020).

This scientific paper explores numerous machine learning algorithms used for sentiment analysis, specifically in social media. The research dives into many levels of sentiment analysis, such as document, sentence, aspect, phrase, and feature level. The authors also address how sentiment analysis may be applied to specific topics, such as analyzing tweets about Alzheimer's illness and spotting email spam using personality identification. The authors examine the performance of several machine learning algorithms, such as Naive Bayes, Random Forest, and SVM, in sentiment analysis. Random forest method using Unigram with Sentiwordnet includes negation words, for example, achieves the greatest accuracy of 95.6%. Overall, this scholarly research gives great insight into the numerous machine-learning approaches utilized in social media sentiment analysis and their applicability in diverse fields (Bhatt and Swarndeep, 2020).

This paper presents a word vector refinement model based on an improved genetic algorithm, which employs improved genetic algorithms to obtain the optimized word vector such that it can be closer to a set of semantically and emotionally similar nearest neighbors and further away from emotionally dissimilar neighbors. Additionally, the model employs a sentiment lexicon to obtain the sentiment ranking of semantic nearest neighbors (Li and Liang, 2020).

This article examines the methodology, platforms, and applications of sentiment analysis in social media from 2014 to 2019, focusing on global events, healthcare, politics, and business. The two main methodologies identified are a lexicon-based approach and a machine learning approach, with most research collecting data on Twitter as the principal platform. Sentiment analysis has applications ranging from disaster response and recovery to detecting security breaches, recognizing sentiment demands during crises, and estimating depression levels. The study addresses prominent sites for information extraction, its extensive uses, and how sentiment analysis is used in many areas (Drus and Khalid, 2019).

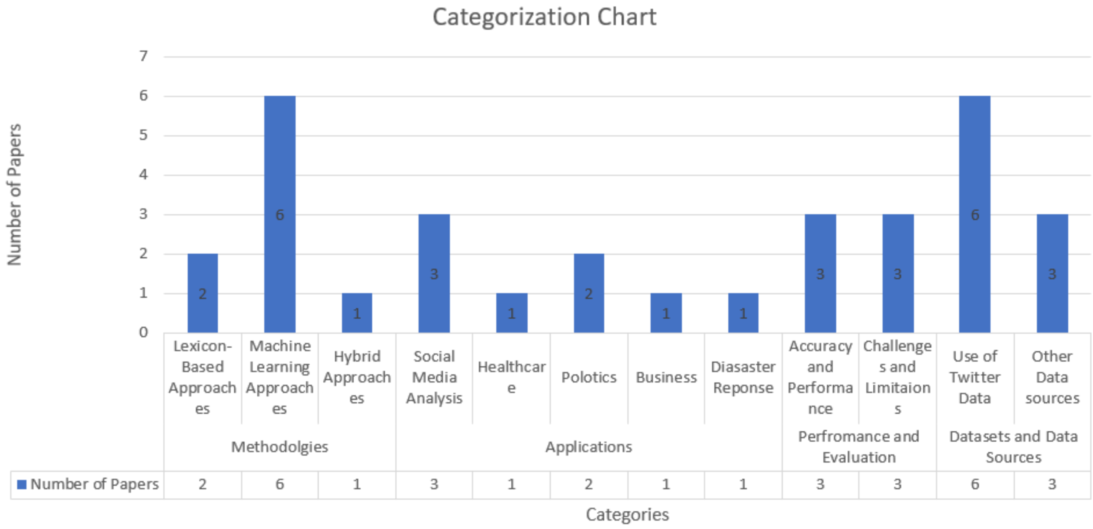

Figure 2 Categorization of a number of papers based on different categories.

Figure 2 categorizes research papers into four key areas: Methodologies (categorized into Lexicon-Based, Machine Learning, and Hybrid Approaches), Applications (covering various domains like social media, Healthcare (Artera, 2021), Politics, Business, and Disaster Response), and Performance and Evaluation (including discussions on Accuracy and Performance, as well as Challenges and Limitations). Additionally, it classifies papers based on their data sources, primarily focusing on the use of Twitter data and other sources.

Table 1 Summary of Research Papers on Sentiment Analysis Techniques

Paper Title	Focus	Methodologies	Findings/Key Points
Machine Learning Approaches for Sentiment Analysis (Tan, Lee, and Lim, 2023)	Machine Learning Approaches in Sentiment Analysis	Various machine learning algorithms, Deep learning models	Comparison of machine learning algorithms and deep learning approaches in sentiment analysis. Challenges in analyzing poorly organized and caustic words, lack of fine-grained sentiment analysis, and potential bias in training data. Importance of more trustworthy language models.

Paper Title	Focus	Methodologies	Findings/Key Points
Strategies for Sentiment Analysis in Textual Data (Appiahene *et al.*, 2022)	Methodologies for Sentiment Analysis	Lexicon-based techniques, Machine learning methods	Sentiment analysis is used to analyze attitudes on LGBTQ+ issues. Positive sentiments outweigh negative thoughts. Importance of sentiment analysis in decision-making.
Machine Learning-based Approaches for Urdu-based Sentiment Analysis (Liaqat *et al.*, 2022)	Machine Learning Approaches for Urdu-based Sentiment Analysis	Machine learning and deep learning approaches, Combination with other techniques	Application of machine learning and deep learning approaches in Urdu-based sentiment analysis. Importance of combining sentiment analysis techniques with other approaches.
Challenges and Approaches in Sentiment Analysis (Gouthamia and Hegde, 2021)	Issues and Approaches in Sentiment Analysis	Challenges in sentiment analysis, Accuracy, and evaluation metrics	Difficulties in determining precise sentiment meaning and polarity. Importance of accuracy, precision, recall, and F-measure in evaluating results. A combination of machine learning and dictionary-based techniques can improve accuracy.
TF-IDF based Sentiment Classification Model (Hassan and Islam, 2021)	TF-IDF based Sentiment Classification	TF-IDF, Sentiment classification model	Development of a sentiment classification model based on TF-IDF with 92% accuracy.
Difficulties and Methodologies in Sentiment Analysis (Hamed, Ezzat, and Hefny, 2020)	Difficulties and Methodologies in Sentiment Analysis	Challenges in sentiment analysis, Combination of machine learning and dictionary-based approaches	Challenges in sentiment analysis, such as sentiment polarity recognition. Importance of sentiment analysis in decision-making.
Improved Genetic Algorithm for Word Vector Refinement in Sentiment Analysis (Li and Liang, 2020)	Word Vector Refinement Model using Genetic Algorithm	Improved Genetic Algorithm, Sentiment lexicon	Use of improved genetic algorithm for word vector refinement in sentiment analysis. Importance of sentiment lexicon for sentiment ranking.
Short-Text Sentiment Analysis using CNN-BiLSTM (Yue and Li, 2020)	Short-Text Sentiment Analysis using CNN-BiLSTM	CNN, Bidirectional Long Short-Term Memory (BiLSTM)	Combined CNN-BiLSTM model for short-text sentiment analysis. Benefits from feature extraction capabilities of CNN and short-term bidirectional text dependency learning capabilities of BiLSTM.
Performance Comparison of Machine Learning Approaches (Poornima and Priya, 2020)	Performance Comparison of Machine Learning Approaches	SVM, Multinomial Naïve Bayes, Logistic Regression	Performance comparison of SVM, Multinomial Naïve Bayes, and Logistic Regression for sentiment analysis. Logistic Regression achieves high accuracy with a bigram model.
RNN for Sentiment Analysis (Goel and Batra, 2020)	RNN for Sentiment Analysis	RNN, Machine learning methods	Comparison of RNN and machine learning methods for sentiment analysis. The superior performance of the RNN model.

4. Methods and Techniques

As was stated in the introduction, Sentiment Analysis has been done in a variety of ways. These methods were divided into three groups: hybrid, machine learning, and lexicon-based. After reading about multiple studies, only one used a hybrid strategy; the others used lexicon- and machine-learning techniques. In almost every study, machine learning methods are employed. The most popular machine learning algorithm was the SVM. In addition, K-NN, decision trees, and Naive Bayes classifiers were applied. Deep learning approaches are very common nowdays as they're very helpful in extracting features. There are several methods and techniques used in sentiment analysis, each with its own set of strengths and limitations. Some of the most used methods and techniques are:

1. Machine learning: To predict the sentiment of new text, machine learning techniques are employed to train models on massive datasets of labeled text. Three

popular methods, Naive Bayes, SVM, and Random Forests, are used for Sentiment Analysis. A large Volume of labeled data is required for training these methods, which is a computationally costly process, but these methods show the potential to be more accurate than rule-based methods (Poornima and Priya, 2020; Bhatt and Swarndeep, 2020; Yaakub, Latiffi, and Zaabar, 2019; Wongkar and Angdresey, 2016; Berawi, 2020).

2. Complex data can be extracted using different CNNs and RNNs, and they can be used to classify text at a more granular level, such as identifying specific emotions or opinions. However, they require Vast amounts of labeled data and can be computationally expensive (Tan, Lee, and Lim, 2023; Yue and Li, 2020)
3. Lexicon-based methods can be useful in cases where training data is limited or when domain-specific knowledge is required. However, they can be limited by the fact that they do not take context into account (Appiahene *et al.,* 2022; Hilario *et al.,* 2021; Drus and Khalid, 2019)

Overall, the choice of method or technique for sentiment analysis will depend on the specific application, available data, and resources. It is important to carefully evaluate the strengths and limitations of each approach before deciding which one to use.

5. Dataset Domains

Datasets are a crucial component of sentiment analysis as they provide the labeled data necessary to train and evaluate sentiment analysis models. It was discovered after analyzing the articles that researchers employed many datasets in different fields. E-commerce applications, movie reviews, tweets, books, items, political battles, and online discussion forums like Quora are some of these domains. The summaries of research papers give insights into the various dataset domains utilized in sentiment analysis investigations. These domains cover a wide range of themes, languages, and sources, demonstrating sentiment analysis's adaptability and application across several areas.

The performance and contextual relevance of sentiment analysis algorithms are substantially impacted by the selection of datasets from domains. Sentiment analysis algorithms can comprehend sentiment expressions, linguistic variants, and contextual nuances better by using domain-specific datasets, which eventually produce more accurate and insightful sentiment analysis results.

6. Evaluation Criteria

Evaluation measures are essential in evaluating the efficacy and performance of sentiment analysis models. This section gives a summary of the most popular evaluation metrics used in SA.

1. Comparison of Different Approaches: You can determine the most efficient strategy for sentiment analysis by comparing various approaches, including supervised learning, ensemble learning, deep learning, and machine learning algorithms (Alsaeedi and Khan, 2019).
2. Performance Metrics: Various performance metrics, including recall, F1 score, precision, and specificity, are used to evaluate the effectiveness of sentiment analysis algorithms. These metrics enable you to assess the models from many angles and comprehend how well they can recognize positive, negative, and neutral attitudes. (Liaqat *et al.*, 2022)
3. The use of domain knowledge Analyzing the use of domain knowledge, such as ontologies, in sentiment analysis can shed light on the accuracy impact and potential advantages of including this data. This criterion emphasizes how well-organized

knowledge representation may be used in sentiment analysis tasks (Goel and Batra, 2020).

4. Technique Comparison: Understanding the relative advantages and disadvantages of various sentiment analysis methods, such as Naive Bayes, SVM, KNN, and deep learning models, can be accomplished by performing a technique comparison. Based on their effectiveness and accuracy, this evaluation criterion helps you to choose the technique that is most appropriate for sentiment analysis jobs (Poornima and Priya, 2020).

7. Challenges

Despite substantial advancements in recent years, sentiment analysis still confronts several difficulties. The following are some of the current difficulties in sentiment analysis:

1. Sentiment analysis models frequently have trouble interpreting the nuances of language used in context, such as sarcasm, irony, or metaphorical terms. These subtleties have a substantial impact on the sentiment expressed in a text, and it is still difficult for sentiment analysis to capture them correctly.
2. Multilingual sentiment analysis: Due to the variations in language structures, sentiment expressions, and cultural cues between various languages, sentiment analysis in multilingual contexts is difficult. It is still difficult to create sentiment analysis algorithms that are reliable and accurate and can handle different languages.
3. Domain-specific sentiment analysis: Sentiment expressions and language usage might change dramatically across different domains, such as product reviews, social media, or healthcare. Hence, sentiment analysis models trained on broad datasets may not perform well in domain-specific situations.
4. Managing noisy and unstructured data: User-generated content, such as posts on social media, reviews on websites, and other user-generated content, frequently contains noise, such as typos, grammatical errors, and colloquial language. Given the lack of linguistic standardization and consistency, sentiment analysis models must be strong enough to manage such noisy and unstructured data.
5. Lack of labeled data: To be trained, sentiment analysis models normally need a lot of labeled data. The acquisition of labeled data, however, can be costly, time-consuming, and resource-intensive. The absence of labeled data, particularly for certain topics or languages, continues to be a barrier to the creation of precise and reliable sentiment analysis models.

8. Future Directions

To develop the field of sentiment analysis, various new paths are now being investigated. Several potential paths for sentiment analysis in the future include:

1. Context-aware sentiment analysis: Creating models for sentiment analysis that can more accurately comprehend and take into account a text's contextual information, such as the words around them, the sentence structure, and the discourse context, in order to accurately capture the nuanced sentiment expressions.
2. Multimodal sentiment analysis: Extending sentiment analysis beyond text and including other modalities, such as audio, visual, and physiological inputs, in order to capture emotions and sentiments communicated through many channels, including facial expressions, tone of voice, and physiological reactions.
3. Deep learning approaches: Exploring more advanced deep learning techniques, such as transformer-based models, graph neural networks, and reinforcement learning, to improve the accuracy and performance of sentiment analysis models, particularly in

capturing long-range dependencies and understanding complex relationships among words and phrases.
4. Real-time sentiment analysis: Developing sentiment analysis models that can process and analyze sentiment in real time, allowing for real-time monitoring of social media, customer feedback, or other streams of data for timely decision-making and response.

9. Discussion

Most studies on sentiment analysis (SA) were tailored to address industry-specific challenges because SA-ready datasets available were often domain-specific, such as movie and tweets datasets. Additionally, because most of the content published on various platforms is written in various styles, creating a corpus takes time and needs specially designed pre-processing tools for SA. Approaches based on machine learning and deep learning were frequently employed to categorize text as good, negative, or neutral. SVM and KNN supervise machine learning algorithms to yield the highest accuracy. The major use of CNN and RNN is feature extraction from text. When classifying large amounts of text data, it has been found that most predictions based on sentiment analysis typically use Naive Bayes (NB) and Neural Network (NN) algorithms.

10. Conclusions

Most of the research in sentiment analysis has focused on machine learning and deep learning techniques to extract features from text and mine messages for insightful information. Sentiment analysis is an effective tool for analyzing user-generated information on social media websites, movie review websites, and e-commerce websites and for helping people make better decisions. However, properly detecting underlying sentiment is difficult due to the intricacies of human language, cultural and contextual impacts, data sparsity and noise, and a lack of universal sentiment markers. This survey's goal was to examine historical patterns in sentiment analysis to assist researchers in addressing issues and potential solutions. This is significant since various fields rely heavily on sentiment analysis for decision-making. The main resources, difficulties, and strategies for sentiment analysis that have been created for data mining jobs were discussed in this review. Additionally, the selection of available datasets is limited to a few industries, including hotels, book reviews, social media comments, tweets, and online retail product reviews. Furthermore, no multi-domain gold-standard dataset is currently accessible. Such a dataset could be created in future research. Sentiment Analysis can be used to profit from more studies and datasets.

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References

Alsaeedi, A., Khan, M.Z., 2019. A Study on Sentiment Analysis Techniques of Twitter Data. *International Journal of Advanced Computer Science and Applications,* Volume 10(2), pp. 361–374

Appiahene, P., Afrifa, S., Kyei, E.A., Nimbe, P., 2022. Understanding the Uses, Approaches and Applications of Sentiment Analysis. *Research Square,* pp. 1–20

Artera, 2021. The Importance of Sentiment Analysis in Healthcare. Available online at https://artera.io/blog/sentiment-analysis-in-healthcare/, Accessed on December 21,

2022
Berawi, M.A., 2020. Managing Artificial Intelligence Technology for Added Value, *International Journal of Technology,* Volume 11(1), pp. 1–4
Bhatt, N.T., Swarndeep, S.J., 2020. Sentiment Analysis using Machine Learning Technique: A Literature Survey. *International Research Journal of Engineering and Technology*, Volume 7, p. 12
Drus, Z., Khalid, H., 2019. Sentiment Analysis in social media and Its Application: Systematic Literature Review. *Procedia Computer Science,* Volume 161, pp. 707–714
Fairlie, M., 2022. How Sentiment Analysis Can Improve Your Sales. Available online at https://www.businessnewsdaily.com/10018-sentiment-analysis-improve-business.html, Accessed on November 28, 2022
Goel, A.K., Batra, K., 2020. A Deep Learning Classification Approach for Short Messages Sentiment Analysis. *In*: 2020 International Conference on System, Computation, Automation and Networking (ICSCAN), pp. 1–3
Gouthamia, S., Hegde, N.P., 2021. A Survey on Challenges and Techniques of Sentiment Survey. *Turkish Journal of Computer and Mathematics Education,* pp. 4510–4515
Hamed, S., Ezzat, M., Hefny, H.A., 2020. A Review of Sentiment Analysis Techniques. International Journal of Computer Applications, Volume 176(37), pp. 20–24
Hassan, R., Islam, M.R., 2021. Impact of Sentiment Analysis in Fake Online Review Detection. *In*: 2021 International Conference on Information and Communication Technology for Sustainable Development, pp. 21–24
Hilario, M., Esenarro, D., Petrlik, I., Rodriguez, C., 2021. Systematic Literature Review of Sentiment Analysis Techniques. *Journal of Contemporary Issues in Business and Government,* Volume 27(1), p. 234100436
Li, J., Liang, Y., 2020. Refining Word Embeddings Based on Improved Genetic Algorithm for Sentiment Analysis. *In*: 2020 IEEE 9th Joint International Information Technology and Artificial Intelligence Conference (ITAIC), Volume 9, pp. 213–216
Liaqat, M.I., Hassan, M.A., Shoaib, M., Khurshid, S.K., Shamseldin, M.A., 2022. Sentiment Analysis Techniques, Challenges, And Opportunities: Urdu Language-Based Analytical Study. *PeerJ Computer Science,* Volume 8, p. e1032
Mehta, P., Pandya, S., 2020. A Review on Sentiment Analysis Methodologies, Practices and Applications. International Journal of Scientific & Technology Research, Volume 9(2), pp. 601–609
Poornima, A., Priya, K.S., 2020. A Comparative Sentiment Analysis of Sentence Embedding Using Machine Learning Techniques. *In*: 2020 6th International Conference on Advanced Computing & Communication Systems (ICACCS), pp. 493–496
Ren, R., Wu, D.D., Liu, T.X., 2018. Forecasting Stock Market Movement Direction Using Sentiment Analysis and Support Vector Machine. *IEEE Systems Journal,* Volume 13(1) pp. 760–770
Repustate, 2022. Benefits of Sentiment Analysis for Impactful Growth. Available online at https://www.repustate.com/blog/sentiment-analysis-benefits/, Accessed on December 20, 2022
Robinson, S., 2021. Sentiment Analysis: Why it's necessary and how it improves CX. Available at https://www.techtarget.com/searchcustomerexperience/tip/Sentiment-analysis-Why-its-necessary-and-how-it-improves-CX, Accessed on December 20, 2022
Siswanto, J., Suakanto, S., Andriani, M., Hardiyanti, M., Kusumasari, T.F., 2022. Interview Bot Development with Natural Language Processing and Machine Learning. *International Journal of Technology,* Volume 13(2), pp. 274–285 Not found in the text
Tan, K.L., Lee, C.P., Lim, K.M., 2023. A Survey of Sentiment Analysis: Approaches, Datasets,

and Future Research. *Applied Sciences,* Volume 13(7), p. 4550
Trends, M., 2020. Types of Sentiment Analysis and How Brands Perform Them. Available at https://www.analyticsinsight.net/types-of-sentiment-analysis-and-how-brands-perform-them/, Accessed on (December 20, 2022)
Techtarget, 2023. Sentiment Analysis (Opinion Mining). Available online at https://www.techtarget.com/searchbusinessanalytics/definition/opinion-mining-sentiment-mining, Accessed on October 30, 2022
Wongkar, M., Angdresey, A., 2016. Sentiment Analysis Using Naive Bayes Algorithm of The Data Crawler: Twitter. *In*: 2019 Fourth International Conference on Informatics and Computing (ICIC), pp. 1–5
Yaakub, M.R., Latiffi, M.I.A., Zaabar, L.S., 2019. A Review on Sentiment Analysis Techniques and Applications. *In*: IOP Conference Series: Materials Science and Engineering, Volume 551(1), p. 012070
Yue, W., Li, L., 2020. Sentiment Analysis using Word2vec-CNN-BiLSTM Classification. *In*: 2020 Seventh International Conference on Social Networks Analysis, Management and Security (SNAMS), pp. 1–5
Zhai, G., Yang, Y., Wang, H., Du, S., 2020. Multi-Attention Fusion Modeling for Sentiment Analysis of Educational Big Data. *Big Data Mining and Analytics,* Volume 3(4), pp. 311–319