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(Review Article)

Sentiment analysis with machine learning and deep learning: A survey of techniques and applications

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Abstract

Sentiment analysis is the task of automatically identifying the sentiment expressed in text. It has become increasingly important in many applications such as social media monitoring, product reviews analysis, and customer feedback evaluation. With the advent of deep learning techniques, sentiment analysis has seen significant improvements in performance and accuracy. This paper presents a comprehensive survey of machine learning and deep learning methods for sentiment analysis at the document, sentence, and aspect levels. We first provide an overview of traditional machine learning approaches to sentiment analysis and their limitations. We then look into various machine learning and deep learning architectures that have been successfully applied to this task. Additionally, we discuss the challenges of dealing with different data modalities, such as visual and multimodal data, and how both techniques have been adapted to address these challenges. Furthermore, we explore the applications of sentiment analysis in diverse domains, including social media, product reviews, and healthcare. Finally, we highlight the current limitations of deep learning approaches for sentiment analysis and outline potential future research directions. This survey aims to provide researchers and practitioners with a comprehensive understanding of the state-of-the-art deep learning techniques for sentiment analysis and their practical applications.

Keywords: Natural Language Processing; Sentiment Analysis; Text Analysis; Recurrent Neural Network; Deep Neural Network; Convolutional Neural Network; Machine Learning; Deep Learning

1. Introduction

Sentiment analysis, a branch of natural language processing, focuses on the automated identification and classification of emotions, opinions, and subjective expressions conveyed through written text [1]. With the exponential rise of social media platforms, the abundance of publicly shared sentiments and viewpoints has increased significantly, rendering sentiment analysis an indispensable tool for gauging public opinion across various domains, including business, politics, and others. This technique involves analyzing diverse sources, such as tweets, reviews, and other forms of user-generated content, to extract valuable insights into prevalent attitudes and perceptions.

Sentiment analysis has proven to be an effective predictor of significant events, such as a movie's box office performance and election outcomes [2]. The process entails evaluating opinions expressed about specific entities, like products, services, individuals, or locations, which can be found on various websites and platforms like Amazon and Flipkart. These opinions are typically categorized as positive, negative, or neutral. The primary objective of sentiment analysis is to automatically determine the sentiment conveyed in user-generated content [3], enabling organizations and decision-makers to understand and respond to public sentiment effectively.

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Moreover, the ever-increasing volume of unstructured data generated on social media platforms has fueled the demand for sentiment analysis techniques capable of analyzing and structuring this vast trove of information [4]. By harnessing sentiment analysis, businesses and organizations can gain a competitive edge by tailoring their strategies and decision-making processes to align with public sentiment, ultimately enhancing customer satisfaction and fostering stronger relationships with their target audiences.

Traditional machine learning techniques have been widely employed for sentiment analysis tasks, involving careful feature engineering and the use of algorithms such as Naive Bayes, Support Vector Machines, and Logistic Regression. However, these methods often struggle to capture the intricacies of natural language and require extensive manual effort in feature extraction. In recent years, deep learning approaches have emerged as powerful alternatives, leveraging their ability to automatically learn discriminative features from raw text data. Architectures like Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNNs) have shown remarkable success in sentiment analysis tasks, effectively modeling the sequential nature of text and capturing long-range dependencies. Furthermore, the advent of pre-trained language models, such as BERT and GPT, has revolutionized the field, enabling transfer learning and achieving state-of-the-art performance on sentiment analysis tasks with relatively smaller datasets. These deep learning techniques have significantly advanced the capabilities of sentiment analysis systems, enabling more accurate and robust analysis of sentiment across various domains and applications. Figure 2 provides a visual representation of the sentiment analysis process.

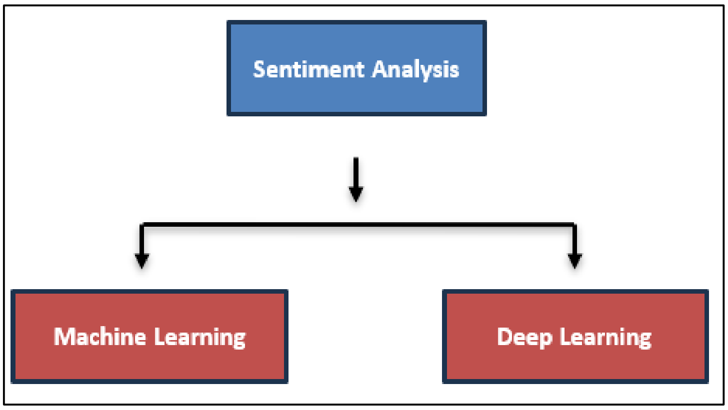

Figure 1 Sentiment analysis approaches can be categorized as machine learning and deep learning.

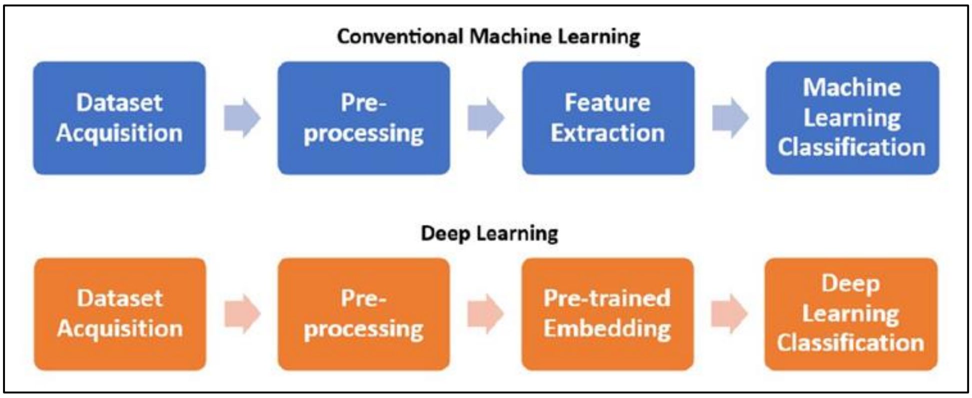

Figure 2 Flow charts of the sentiment analysis process using conventional machine learning, and deep learning approaches.

In this comprehensive survey, we provide an in-depth exploration of both traditional machine learning and modern deep learning approaches for sentiment analysis tasks. We discuss conventional machine learning techniques like Naive Bayes, Support Vector Machines, and Logistic Regression, as well as deep learning architectures such as recurrent neural networks (RNNs), long short-term memory (LSTM) networks, convolutional neural networks (CNNs), and attention-based models. We examine the challenges of multimodal sentiment analysis and how deep learning models address them. Additionally, we explore the practical applications of sentiment analysis across domains like social media, product reviews, and healthcare. Finally, we outline the current limitations and future research directions, including handling context, sarcasm, domain adaptation, interpretability, and model robustness in machine learning and deep learning for sentiment analysis.

The rest of the paper is organized as section II provides a literature survey of state of art systems for sentiment analysis using machine learning and deep learning models. Section III provides a discussion and section IV concludes the paper with future research directions.

2. Literature Survey

Machine learning and deep learning are two areas of artificial intelligence that have become very popular lately. Machine learning is a way of analyzing data that helps computers build models to make predictions or decisions without being manually programmed. Deep learning, which is a part of machine learning, uses neural networks to handle more complicated tasks. These models are inspired by how the human brain works and can learn from data that isn't neatly organized or labeled[5-11].

There has been a lot of research and progress in machine learning and deep learning, especially as computers have gotten faster and more data has become available. One of the biggest benefits of these technologies is that they can learn from data on their own, without needing to be explicitly programmed. This makes them very useful for tasks like recognizing images and speech, understanding natural language, and making recommendations[12-19].

In recent years, the increase in data and better computing power has led to more advanced algorithms and models in machine learning and deep learning. This has resulted in significant breakthroughs in many industries, showing just how powerful these technologies can be in solving real-world problems[20-24].

2.1. Machine learning approaches

Researchers in [25] utilized a cut-based approach for subjectivity classification on a movie review dataset. The cut-based subjectivity detectors identified subjective portions of documents by examining pair-wise relationships and per-item information. Initially, they extracted the subjective sections from the review documents and classified them into subjective and objective categories using a minimum-cut framework. The experiments demonstrated that employing a minimum-cut framework enhanced the effectiveness of sentiment analysis.

In a comparative experiment detailed in [26], different machine learning classifiers were tested on a product reviews dataset. The study employed both a generative model and a discriminative algorithm for classification, specifically testing the winnow algorithm [27]. The findings indicated that Naive Bayes (NB) outperformed Support Vector Machines (SVM) when using unigram features on datasets other than movie reviews. The results also revealed that high-order n-grams could help differentiate article polarity in mixed contexts. However, the authors noted that a large number of n-grams could introduce noise, suggesting the need for a better feature selection method.

In [28], the authors addressed a sentiment analysis model in the medical field using an SVM classifier and a language model. Instead of identifying personal opinions, they extracted polarity information from medical outcomes in patient records. A small lexicon of medical domain words was manually compiled. By incorporating domain knowledge and linguistic features, the model's performance was enhanced.

The paper in [29] compared SVM and Naive Bayes sentiment classifiers on a Cantonese review dataset. Various n-gram representations, including unigram, bigram, and trigram with frequency features, were used to study the impact of feature size and representation on classification performance. The results showed that the NB classifier achieved better performance than SVM, with a 95.67% accuracy for 900-1100 features. Similarly, researchers in [30] compared lexicon-based, machine learning, and deep learning methods for sentiment analysis on Manipuri video review comments. Their manually categorized dataset of 4000 comments, collected from social media, revealed that the NB classifier outperformed others. Another study [31] introduced a sentiment analysis system for Manipuri news using a machine learning approach. Data were gathered from local newspapers, and language-specific preprocessing tasks, such as transliteration, building a negative morpheme-based lexicon, and filtering out noisy words, were performed. These efforts improved the system's robustness and achieved the highest accuracy.

In 2019, a novel approach to sentiment analysis was introduced by combining boosting and bagging methods within an AdaBoost model[32]. This study focused on analyzing US airline Twitter data, which was preprocessed to remove irrelevant information and then analyzed using data-mining techniques. A 75-25 data split was used, with 75% for training and 25% for testing, resulting in an F-score of 68% for the AdaBoost model.

Another 2019 study applied the ridge classifier method to sentiment analysis on the IMDb and Sentiment140 datasets[33]. The preprocessing stage included tokenization, case folding, and the removal of URLs, HTML tags, and irrelevant words, with the data represented using the TF-IDF method. The ridge classifier achieved 90.54% accuracy on the IMDb dataset and 76.84% on the Sentiment140 dataset, demonstrating its effectiveness.

A study in 2020 aimed to improve sentiment analysis accuracy for Arabic Tweets using the multinomial naive Bayes method on a dataset of 2000 labeled Tweets[34]. Preprocessing involved tokenization using 4-grams and stemming with the Khoja stemmer, with the data represented as TF-IDF features and classified using a fivefold cross-validation process, achieving an accuracy of 87.5%.

In a comprehensive 2020 study, sentiment analysis of US airline Twitter data was conducted using six different machine learning models: support vector machine (SVM), logistic regression, random forest, XgBoost, naive Bayes, and decision tree[35]. The data underwent preprocessing including stop-word removal, punctuation removal, case folding, and stemming. Feature extraction was performed using the bag-of-words method on a dataset from CrowdFlower and Kaggle, containing 14,640 samples with three sentiment classes: positive, negative, and neutral. SVM achieved the highest accuracy of 83.31%, followed by logistic regression at 81.81%, using a 70% training and 30% testing split.

In 2021, a study on sentiment analysis related to violence against women utilized several machine-learning models, including SVM, k-nearest neighbor, naive Bayes, and decision tree[36]. The dataset, collected from Arabic Tweets, was preprocessed with tokenization, stemming, and stop-word removal, and feature extraction was done using the TF-IDF method. SVM achieved the highest accuracy of 78.25%.

Another 2021 study developed a sentiment analyzer to classify text polarity with high accuracy using naive Bayes, multinomial naive Bayes, Bernoulli naive Bayes, logistic regression, and linear support vector classification methods[37]. The 'Twitter samples' corpus from the Natural Language Toolkit, consisting of 10,000 Tweets with equal numbers of positive and negative Tweets, was used. Preprocessing included tokenization, stop-word removal, URL removal, symbol removal, case folding, and lemmatization. The naive Bayes method achieved the highest accuracy of 99.73%, making it the best-performing algorithm in the study.

2.2. Deep Learning Approaches

The deep learning-based sentiment analysis model has gained popularity due to its exceptional performance. Deep learning, an emerging area within machine learning, offers both supervised and unsupervised feature representation approaches[38]. This technique utilizes multiple perceptron layers, inspired by the human brain[39]. A foundational contribution to deep learning was made in 2006 with the introduction of a deep belief network[40]. One notable deep learning model, the Recursive Neural Tensor Network (RNTN), was developed for sentence-level sentiment classification by modeling the composition of phrases. This model was used alongside the Stanford Sentiment Treebank corpus, which includes parse trees annotated with sentiment[41]. Fine-tuning a pre-trained network often yields better performance compared to using a feature vector alone, as it better captures discriminative information[42].

In one study, researchers adopted a convolutional neural network (CNN) architecture for textual sentiment classification[43]. Their system combined an embedding layer, two convolutional layers, a pooling layer, and a fully connected layer. Using datasets of customer reviews, movie reviews, and the Stanford Sentiment Treebank, they compared traditional machine learning classifiers to their deep neural architecture. Their findings showed that the parallel CNN architecture reduced computational overhead and improved classification accuracy, particularly with long texts.

Researchers continue to integrate various deep-learning techniques for sentiment classification. One study combined different deep learning architectures into a single framework, using pre-trained word vectors as input along with a convolutional neural network (CNN) and long short-term memory (LSTM) layers[44]. This combination leverages CNN for local text features and LSTM for context-dependent features, resulting in superior performance compared to existing LSTM, CNN, CNN-LSTM, and SVM classifiers.

Another study reported a document-level sentiment analysis framework using a deep CNN and bidirectional LSTM (BiLSTM) on French news articles[45]. The CNN extracted local features, which were then fed into a BiLSTM. After applying multiple filters and max pooling, the concatenated results were input into a fully connected layer, with a softmax function used for classification. This method achieved high performance in sequence classification tasks on long texts.

In research focused on code-mixed languages, a convolutional neural network was applied to a Bengali-English dataset, as well as a monolingual Telugu dataset[46]. The code-mixed Bengali data achieved higher accuracy compared to the Telugu dataset, likely due to the morphological richness of Telugu, which increases the likelihood of words having the same meaning. Another framework utilized CNN and LSTM-based ensemble models to detect Hinglish hate speech on social media, reporting an F-Score of 0.617 on the test data[47].

Recent studies have begun incorporating attention mechanisms to enhance performance. A hierarchical attention mechanism was used in a document-level sentiment classification model to focus on the essential content of documents, resulting in improved performance on text-based review datasets[48]. Another study addressed the challenge of generating semantic relationships between sentences in a document by developing the SR-LSTM model, which uses LSTM layers to extract sentence vectors and recognize inter-sentence relationships[49].

In a 2017 study, sentiment analysis was performed on a dataset of 4000 Tweets in both Korean and English. The preprocessing phase included tokenization, case folding, stemming, and the removal of stop words, numbers, and punctuation marks. A multilayer perceptron (MLP) model with three hidden layers, optimized using Stochastic Gradient Descent (SGD), achieved an accuracy of 75.03% on the dataset [50].

Similarly, a 2019 study utilized an MLP model for sentiment analysis on Turkish Tweets containing the hashtag "15Temmuz". The dataset consisted of 3000 positive and negative Tweets. The preprocessing phase included Turkish deASCIIfication, tokenization, stop-word and punctuation removal, and stemming. The word2vec pre-trained model was used to convert the text into embeddings, which served as inputs to the MLP with six dense layers and three dropout layers, achieving an accuracy of 81.86% [51].

In 2021, an MLP was used for sentiment analysis on COVID-19-related Tweets, which included 101,435 Tweets. The data were preprocessed to remove HTML tags and non-letters and to tokenize and stem the text. Text data were represented using a count vectorizer and TF-IDF vectorizer, and classified using an MLP model with five hidden layers and ReLU activation. The count vectorizer representation with MLP achieved the highest accuracy of 93.73% [52].

A 2018 study compared several machine learning and deep learning methods for sentiment analysis using the IMDb dataset containing 3000 reviews. The text was preprocessed to remove irrelevant characters, symbols, repeating words, and stop words, then represented using the count vectorizer. The CNN model achieved the highest accuracy of 99.33% [53].

In 2020, machine learning and deep learning methods were compared for sentiment analysis using Sentiment140 and Twitter US Airline Sentiment datasets. Preprocessing included tokenization, case folding, and the removal of stopwords, URLs, hashtags, and punctuation. Methods compared included multinomial naive Bayes, logistic regression, SVM, LSTM, and an ensemble of multinomial naive Bayes, logistic regression, and SVM with majority voting. LSTM recorded the highest accuracy of 82% on Sentiment140, while SVM achieved 68.9% on the Twitter US Airline Sentiment dataset [54].

Sentiment analysis of 5000 Bangla Tweets using LSTM was conducted in 2019. The data were preprocessed by removing spaces and punctuation marks and splitting the dataset into 80% training, 10% validation, and 10% testing. An LSTM architecture with five layers, each with a size of 128, a batch size of 25, and a learning rate of 0.0001, achieved an accuracy of 86.3% [55].

Another 2019 study analyzed sentiment in the Saudi dialect using LSTM and BiLSTM models. The dataset consisted of 60,000 Tweets with positive and negative sentiments. Preprocessing involved removing numbers, punctuation, special symbols, and non-Arabic letters. Text was normalized and encoded using a word2vec pre-trained model for word embedding. The dataset was split into 70% training and 30% testing, with BiLSTM achieving 94% accuracy [56]. A recurrent neural filter-based CNN and LSTM model for sentiment analysis was proposed in 2018. The model utilized an RNN as a convolutional filter and was trained and tested using the Stanford Sentiment Treebank dataset, encoded using GloVe word embedding. The model included an embedding layer, pooling layer, and LSTM layer, using the Adam optimizer and early stopping to prevent overfitting, achieving an accuracy of 53.4% [57].

A hybrid model combining CNNs and LSTM was proposed in 2019. The data comprised 32,000 Tweets from the International Workshop on Semantic Evaluation competition. Preprocessing involved removing URLs, emoticons, and special characters and converting text to lowercase. The hybrid model leveraged word2vec and GloVe embeddings, with the CNN and LSTM models achieving 59% accuracy [58]. In 2020, a Bi-LSTM model was introduced for sentiment analysis on Twitter data using the Twitter US Airline Sentiment dataset. Preprocessing included tokenization and the removal of stopwords and punctuation. Text was represented using word2vec, GloVe, and sentiment-specific embeddings, with the Bi-LSTM model achieving 81.20% accuracy [59].

A Bi-LSTM model for analyzing Amazon e-commerce reviews was proposed in 2021. The dataset contained 23,485 reviews divided into negative, neutral, and positive classes. Data were cleaned by tokenizing and removing special characters, followed by word2vec embedding. The BiLSTM model achieved an accuracy of 90.26% [60]. Similarly, a character-based deep bidirectional long short-term memory (DBLSTM) method was used for analyzing Tamil Tweets in 2020. The dataset contained 1500 Tweets divided into positive, negative, and neutral classes. Preprocessing involved removing unnecessary symbols and characters, with word2vec embedding used for DBLSTM, achieving 86.2% accuracy [61].

A sentiment analysis bidirectional long short-term memory (SAB-LSTM) model was proposed in 2020. The model included 196 Bi-LSTM units, 128 embedding layers, 4 dense layers, and a softmax activation classification layer. The dataset of 80,689 samples from various sources was divided into 90% training and 10% testing, with SAB-LSTM outperforming traditional LSTM models [62]. Lastly, a 2021 study explored the use of RNNs for sentiment analysis of customer reviews from hotel booking websites. Preprocessing involved lemmatization, stemming, and the removal of punctuation and stop-words. The LSTM and GRU models, with 30 and 25 hidden layers respectively, achieved accuracies of 86% and 84% on the dataset [63].

Table 1 Comparative Analysis of state of art the of systems

Authors	Dataset	Preprocessing Techniques	Model	Accuracy
[22]	4000 Tweets (Korean & English)	Tokenization, case folding, stemming, stop words, numbers, punctuation removal	MLP with SGD (3 hidden layers)	75.03%
[23]	3000 Turkish Tweets (#15Temmuz)	Deasciification, tokenization, stop-word and punctuation removal, stemming	MLP with word2vec (6 dense layers, 3 dropout layers)	81.86%
[24]	101,435 COVID-19 Tweets	HTML tags removal, tokenization, stemming, count vectorizer, TF-IDF vectorizer	MLP with ReLU (5 hidden layers)	93.73%
[25]	IMDb dataset (3000 reviews)	Removal of irrelevant characters, symbols, repeating words, stop words, count vectorizer	CNN	99.33%
[26]	Sentiment140, Twitter US Airline Sentiment	Tokenization, case folding, stop-words, URLs, hashtags, punctuation removal	LSTM, SVM, multinomial naive Bayes, logistic regression, ensemble model	82% (Sentiment140), 68.9% (US Airline)
[27]	5000 Bangla Tweets	Space and punctuation removal, 80-10-10 train-validation-test split	LSTM (5 layers, 128 size)	86.3%
[28]	60,000 Saudi Tweets	Numbers, punctuation, special symbols, non-Arabic letters removal, normalization	LSTM, BiLSTM with word2vec	94%
[29]	Stanford Sentiment Treebank	GloVe word embedding	RNN as a convolutional filter	53.4%

[30]	32,000 Tweets (International Workshop on Semantic Evaluation)	URLs, emoticons, special characters removal, lowercase conversion	Hybrid CNN and LSTM with word2vec and GloVe	59%
[38]	Twitter US Airline Sentiment	Tokenization, stop-words, punctuation removal	Bi-LSTM with word2vec, GloVe, sentiment-specific embeddings	81.20%
[39]	23,485 Amazon reviews	Tokenization, special characters removal, word2vec embedding	BiLSTM	90.26%
[40]	1500 Tamil Tweets	Unnecessary symbols, characters removal, word2vec embedding	DBLSTM	86.2%
[41]	80,689 samples from various sources	-	SAB-LSTM with 196 Bi-LSTM units, 128 embedding layers, 4 dense layers, softmax activation	-
[42]	Customer reviews from hotel booking websites	Lemmatization, stemming, punctuation, stop-words removal	LSTM, GRU (30 and 25 hidden layers)	86% (LSTM), 84% (GRU)

3. Discussion

The literature survey reveals significant advancements in sentiment analysis driven by both traditional machine learning and deep learning techniques. Traditional models, such as Naive Bayes and Support Vector Machines, are effective in certain contexts, particularly when paired with robust feature selection methods like n-grams and TF-IDF representations. These methods are foundational in preprocessing, which includes tokenization, stop-word removal, and stemming. However, deep learning approaches, including Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, have demonstrated superior performance due to their ability to handle complex, high-dimensional data. The use of pre-trained word embeddings, such as word2vec and GloVe, has significantly enhanced these models by providing rich semantic information. Advanced techniques like attention mechanisms and hierarchical models have further improved sentiment analysis by enabling a more nuanced understanding of textual data. The survey indicates that model selection and preprocessing techniques must be tailored to the specific dataset characteristics, including language and domain-specific nuances. Overall, while traditional machine learning models are valuable for their simplicity and effectiveness, deep learning models are leading the way in achieving higher accuracy and robustness, showing great promise for future advancements in sentiment analysis across various domains and languages.

4. Conclusion

In this paper we present a comparative analysis of state-of-the-art systems for sentiment analysis, The analysis techniques highlight the strengths and weaknesses of both traditional machine learning and deep learning approaches. Traditional methods like Naive Bayes and Support Vector Machines have shown reliable performance, especially with well-curated feature extraction techniques. However, the advent of deep learning models such as CNNs and LSTMs has revolutionized sentiment analysis, offering superior accuracy and the ability to process complex and voluminous data more effectively. The incorporation of pre-trained embeddings like word2vec and GloVe has further enhanced model performance by providing a richer semantic understanding of the text. Despite these advancements, it is evident that the choice of model and preprocessing steps must be contextually adapted to the specific dataset and language intricacies to achieve optimal results.

In the future, the refinement of deep learning models will be essential to handle the growing complexity of language and sentiment expression in sentiment analysis. Integrating sophisticated attention mechanisms and hierarchical models can better capture nuanced relationships within text data. Expanding research into multilingual sentiment analysis and code-mixed language processing will address challenges in diverse linguistic contexts. Developing real-time applications for dynamic environments, such as social media monitoring and customer feedback systems, will require models to quickly adapt to new data. Incorporating domain-specific knowledge can enhance the accuracy of sentiment analysis in specialized fields like healthcare, finance, and legal analysis. Addressing ethical considerations and biases in sentiment analysis models will be crucial to ensure fair and unbiased decision-making.

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