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Survey Article

The Power Of Opinions: Exploring Sentiment Analysis Techniques & Trends

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Abstract: Sentiment Analysis (SA) is a method used to analyze sentiment and opinions within textual data. It is extensively utilized across multiple industries, including business, healthcare, education, finance, and social media. This study examines various approaches to sentiment analysis, such as machine learning-based, lexicon-based, and hybrid techniques. Machine learning models, such as Support Vector Machines (SVM) and Naïve Bayes, are widely adopted but face challenges in understanding deeper contextual meanings. On the other hand, deep learning techniques like Long Short-Term Memory (LSTM) and Convolutional Neural Networks (CNN) improve accuracy by recognizing intricate text patterns. Hybrid approaches, which integrate machine learning with lexicon-based methods, enhance both interpretability and adaptability.

This study also highlights emerging trends in sentiment analysis, such as emotion-based classification, aspect-based sentiment analysis, and the implementation of transformer-based models like BERT. Despite these advancements, challenges like sarcasm detection, real-time sentiment processing, and multilingual sentiment analysis persist. Addressing these challenges with advanced AI models, transfer learning, and domain-specific sentiment lexicons is essential for future improvements. As sentiment analysis continues to evolve, integrating deep learning, hybrid techniques, and transformer-based models will lead to better contextual understanding. Overcoming existing limitations will make the way for more accurate and profound sentiment analysis applications.

Keywords: Sentimental Analysis, Machine Learning, Deep Learning, Healthcare, E-Commerce, social media, Finance, NLP, BERT, Hybrid Models.

1. Introduction

Sentimental Analysis (SA) or Opinion Mining (OM) is the process of using computers to study people's opinions, feelings, and emotions about something. This "something" could be a person, an event, or a topic often discussed in reviews. The terms SA and OM are usually used interchangeably, meaning they refer to the same thing. However, some researchers believe they have slight differences. Opinion Mining focuses on finding and analyzing what people think about a topic, while Sentimental Analysis looks at the emotions conveyed in a text and then examines them [1]. Sentiment classification aims to decide if a text document has a positive, negative or neutral tone. This is widely used in business to analyze customer feedback and improve products or services [5]. It is an important part of Natural Language Processing (NLP), a subfield of computer science and artificial intelligence that enables computers to understand and interact with human language. Sentimental analysis is especially useful for businesses, stock market analysts, and election-related studies [3]. Sentiment analysis approaches can generally be divided into three categories: machine learning, lexicon-based, and hybrid approaches.

The rest of the paper is described below: Section 2 is the literature review that provides overviews of prominent sentiment analysis techniques, uses, and challenges. Section 3 is an observation of different approaches, showing trends and efficacy across industries. Section 4 summarizes the research by providing conclusions on results, limitations, and potential improvements for future research. Finally, Section 5 is a list of references that support the study's analysis and discussions.

2. Theory

2.1 Techniques In Sentiment Analysis

2.1.1 Machine Learning Approaches

Machine learning methods involve training an algorithm on a set of known data before using it on real-world data. These techniques first teach the algorithm using specific inputs with known outputs, allowing it to make predictions on new, unseen data later [3]. Machine learning methods classify text using training and test datasets. Important features include word presence and frequency, part of speech details, and negations. A key advantage is their ability to adapt and develop models for specific tasks and contexts. However, their effectiveness on new data is limited since they require labeled training data, which can be expensive or difficult to obtain [2].The most frequently used machine learning algorithms include Support Vector Machines (SVMs), Naive Bayes, K-Nearest Neighbors (KNN), Random Forest and Deep learning models [3].

Types of Machine Learning Models:
a. Support Vector Machines: The algorithm works very well with structured data and manages to classify high-dimensional texts with great accuracy [3].
b. Naive Bayes: Algorithm is simpler and works well with small datasets. Maximum Entropy doesn't assume feature independence, making it suitable for complex data [3].
c. Deep Learning: Deep learning has proven highly effective in sentiment analysis, often outperforming traditional machine learning models. However, selecting the best deep-learning model structure for a particular dataset remains challenging.

According to Seo et al. (2020), the following points highlight key concepts about deep learning models used for sentimental analysis:

1. **Convolutional Neural Network (CNN):** CNN was basically developed for processing images, but now it has been applied for text classification, which uses variances of filters applied on the resulting matrix of word or character embeddings for feature extraction.
   There are different types of CNN models:
   1) **Single-layered CNN**: A shallow architecture with one convolution layer followed by max pooling.
   2) **Nine-layered CNN**: A deeper CNN model with six convolution layers followed by three fully connected layers.
   3) **Twenty-Nine-Layered CNN**: The 29-layered CNN is an extremely deep three-dimensional convolutional neural network consisting of 29 convolutional layers and able to obtain short-and-long-range text dependencies.
2. **Recurrent Neural Networks (RNN):** RNNs are capable of processing series of data, which makes them efficient in applications like sentiment classification. Advanced variants include LSTM and GRU networks to overcome the problems of long-time dependencies.
   The study evaluates five RNN-based models:
   1) Vanilla RNN: The basic architecture of an RNN that is build negative of the long-time dependency problems, which surface mainly as a result of gradient norm explosion or vanishing.
   2) Long Short-Term Memory (LSTM): This is a Recurrent Neural Network (RNN) really geared to memories with cell structures that control the use of long-term dependencies.
   3) Grated Recurrent Unit (GRU): A simplified version of LSTM that reduces computational complexity while retaining performance.
   4) Bidirectional LSTM: An enhanced version of LSTM that handles input sequences by analyzing them in both forward and backward directions.
   5) Bidirectional GRU: Similar to the bidirectional LSTM but with GRU cells.

Accuracy: Supervised machine learning techniques, when combined with SVM and deep learning models, achieve varying levels of accuracy. When trained on large, domain-specific datasets, they typically achieve accuracy between 80% and 90% [2].

Challenges of Machine Learning Techniques: There is a chance that these techniques might be disastrous when used for the first time in the context of any implementation other than the one where they were actually trained unless retrained in a new domain.

Requires large labeled dataset: A large-sized mammoth labeled dataset is a costly business. Models might miss out on very critical elements of context, particularly those involving subtleties of sarcasm [2].

2.1.2 Lexicon-Based Approaches
The lexicon-based method of sentiment analysis is one of the key methods adopted to classify the sentiment polarity (positive, negative, or neutral) of textual content [4]. Unlike machine learning methods, which rely on large, manually-labeled datasets for training, the lexicon-based approach uses preset dictionaries or lexicons which contain words annotated with their corresponding sentiment values [3]. It's one advantage is its broad capability to cover a large number of words. However, it is limited by the finite number of words available in a dictionary, with fixed orientations assigned to each word in terms of sentiment, which may not always capture context or evolving language use [3].

Types of Lexicon-based Approaches:
According to Sadia et al. [4], lexicon-based sentimental analysis primarily relies on predefined dictionaries to allocate sentiment values to words. This method can be categorized into two main approaches:

Dictionary-based Approach: This method uses predefined dictionaries or lexicons such as **WordNet** or **SentiWordNet**. These dictionaries are created by human annotators and contain words with assigned sentiment values.

WordNet: A well-known lexical database of English words, which provides semantic relations between words (e.g., synonyms and antonyms). In the terms of sentiment analysis, WordNet is often used to specify whether a word carries a positive or negative sentiment.

Advantages: Simple and easy to implement, especially when a domain-specific dictionary is available.

Drawbacks: It may lack flexibility, as the lexicon often does not adapt to new or evolving words (e.g., internet slang, acronyms). Also, sentiment words may vary significantly across different domains (e.g., a word positive in one domain may be negative in another).

Corpus-Based Approach: In this approach, a large corpus (collection of text documents) is used to generate sentiment lexicons based on statistical methods or semantic techniques.

Statistical Approach: It uses co-occurrence statistics between words in a large dataset to identify sentiment words. For example, words frequently occurring with "good" are likely positive.

Semantic Approach: This approach focuses on the semantic similarity of words to known sentiment words. It can expand the lexicon by including synonyms, antonyms, and similar words based on context.

Advantages: More flexible and can adapt to different domains by using domain-specific corpora.

Drawbacks: Requires a large and representative corpus for effective performance. Additionally, it still may face difficulties in handling domain-specific expressions or slang.

Accuracy: Lexicon-based systems have a precision between 70-80%, depending on the lexicon. They are certainly less accurate on complex datasets, but they are more human-understandable in any low-resource scenario [2].

Challenges of Lexicon-based Approaches: The conveyed sentiment remains static and does not account for transitions. Lexicons often fail to capture emerging slang or domain-specific vocabulary. Additionally, subtle or figurative expressions like irony and sarcasm are particularly challenging to interpret accurately in sentiment analysis [2].

2.1.3 Hybrid Approaches

Hybrid methodologies combine machine learning with lexicon-based strategies. Each has its own strengths, but their integration can lead to even greater advantages [7]. However, challenges remain, particularly in handling disorganized reviews and certain types of user-generated content.

Machine Learning with Lexicon Enhancements: This approach incorporates sentiment scores from dictionaries into a machine learning framework, improving the ability to detect sentiment in text. It can be as straightforward as using the sentiment associated with a word from a lexicon to provide more specificity in the analysis [41].

Sentiment concept-level analysis goes beyond word-level analysis; it is contextual. This method seeks a deeper understanding of sentiment by examining the meanings and relationships between words, enabling the model to grasp the context better. For instance, it helps interpret what "not bad" might imply [41].

Ensemble Models: These models combine various machine learning algorithms with lexicon-based methods, using voting or averaging systems to enhance prediction accuracy. Ensemble models can capture more nuanced sentiment variations, as they are not limited to a single approach [41].

Accuracy: Hybrid models typically achieve accuracy rates between 85-95%, leveraging the strengths of lexicons while benefiting from the adaptability of machine learning [2].

Challenges of Hybrid Approaches:

Complex Implementation: Hybrid models are more challenging to set up and maintain.

Sensitivity to Noisy Data: The end-user environment can introduce noise, which may compromise the accuracy of hybrid models.

Table 1. Comparative Analysis of Techniques

Technique	Strengths	Limitations	Accuracy Range
Machine Learning	High adaptability, strong models	Needs huge categorized datasets	80–90%
Lexicon-Based	Simple, cost-effective	Static, context-insensitive	70–80%
Hybrid	Combines strengths of both	Complex implementation	85–95%

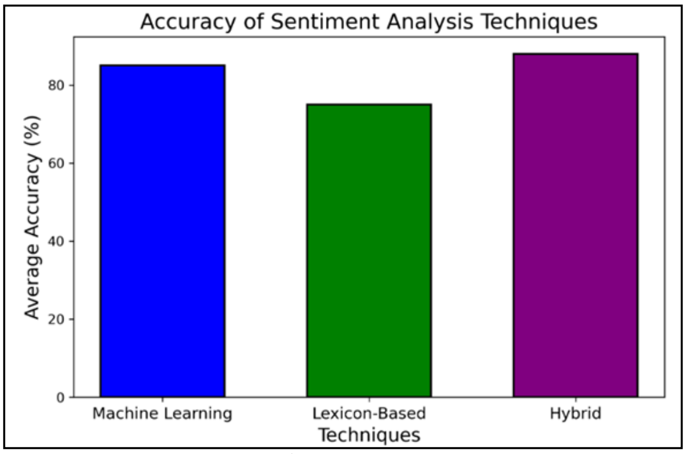

Figure 1. Accuracy of Sentiment Analysis Techniques

2.2 Emerging Trends in Sentimental Analysis

According to Medhat et al. (2014) [1], several emerging trends in sentiment analysis have enhanced the ability to interpret textual data more accurately. These trends focus on capturing deeper insights beyond simple positive or negative classifications.

Emotion-Based Analysis: Instead of broadly classifying sentiment as positive or negative, this approach identifies specific emotions such as happiness, anger, disappointment, or frustration. This prevents oversimplification and allows for a more precise understanding of user experiences. For instance, recognizing whether a customer feels "frustrated with customer service" versus simply "unhappy" enables businesses to tailor responses more effectively.

Aspect-Based Sentiment Analysis: This method analyzes individual aspects of a product or service rather than evaluating an entire review as a whole. For example, a customer might praise "battery life" but criticize "camera quality", offering businesses targeted insights into what customers like or dislike. This detailed understanding helps refine specific features rather than making broad assumptions about overall sentiment.

Transfer Learning: This technique leverages pre-trained models from one dataset and applies them to another, making sentiment analysis more adaptable across different domains. Since a model trained on social media reviews may not work well for financial news sentiment, transfer learning allows it to apply knowledge without retraining from scratch. This method significantly enhances accuracy and efficiency in sentiment classification across diverse fields.

2.3 Challenges in Sentimental Analysis

Sarcasm and Irony Detection: Understanding sarcasm and irony is one of the biggest challenges in sentiment analysis. For example, a sentence like "Great, another traffic jam!" may sound positive but actually expresses frustration. Current models often misinterpret such statements, leading to inaccurate sentiment classification. To improve this, better algorithms and greater contextual awareness are needed.

Real-Time Analysis: There is a growing demand for instant sentiment analysis, especially for live tweets or breaking news. However, analyzing large amounts of data in real time requires significant computational power, making it expensive and resource-intensive. If this challenge is overcome, real-time sentiment analysis could be highly valuable for disaster response and trend monitoring.

Multilingual Sentiment Analysis: While sentiment analysis works well for major languages like English, many fewer common languages lack enough data and models for accurate sentiment classification. This creates a gap in understanding user sentiment across different languages. To solve this, researchers need to develop better datasets and pre-trained models for underrepresented languages.

3. Literature Review

Singh et al. [08] used an LSTM-RNN model with attention layers on 170,000 COVID-19 tweets, achieving a 10% accuracy and precision improvement over SVM and Random Forest. The study applied TF-IDF feature extraction and hyperparameter tuning, identifying 45% positive, 30% neutral, and 25% negative sentiments. However, it lacked real-time analysis, multilingual support, and nuanced sentiment detection. Future work should explore transformer-based models for improved performance.

Chakrapani et al. [09] analyzed patient sentiments in acute disease cases using SVM, Naive Bayes, and Random Forest classifiers. Support Vector Machine achieved 98.2% accuracy in detecting negative sentiments, making it the most effective model. The study incorporated N-gram tokenization and Latent Dirichlet Allocation (LDA) for topic modeling, but suffered from simplistic polarity scoring, reliance on social media data, and lack of deep learning integration. Shubhangi et al. [10] explored text, audio, and video-based sentiment analysis to detect depression and mental health disorders. They employed Naive Bayes, CNN, and LSTM, along with Google Speech-to-Text API for audio sentiment extraction and OpenCV for facial emotion recognition. Key limitations included low accuracy in depression detection, multimodal data integration challenges, and limited use of deep learning techniques like transformers. Bemila et al. [11] applied an RNN-BiLSTM model on Drugs.com reviews, achieving 83% accuracy in sentiment-based drug recommendations. The model used feature extraction techniques like the Bag-Of-Words model to classify reviews as positive or negative. However, limitations included bias in online review data, lack of temporal analysis for evolving drug efficacy, and absence of personalized recommendations based on patient medical history. Clark et al. [12] conducted sentiment analysis on 5.3 million breast cancer-related tweets, using CNN and logistic regression. The study effectively captured patient-reported experiences, achieving 97.6% accuracy in sentiment classification. While it successfully analyzed emotional trends and patient perceptions, challenges included difficulty in detecting sarcasm, potential biases in social media data, and over-reliance on English-language tweets. Yang et al. [13] proposed a GAN-based model to improve sentiment analysis on imbalanced student feedback datasets. The study applied Decision Tree, Naïve Bayes, AdaBoost, SVM, RNN, BiLSTM, CNN, and GRU to evaluate sentiment classification before and after dataset balancing. GAN-balanced datasets improved the F1-score by 2.79% to 9.21% and accuracy by 2.04% to 4.82%, with LSTM and GRU benefiting the most. However, the study had limited exploration of transformer-based models, a narrow focus on the education domain, and a need for structured datasets. Sivakumar et al. [14] performed aspect-based sentiment analysis (ABSA) on student feedback from Twitter using Decision Tree, SVM, and Naïve Bayes, with Naïve Bayes achieving 81.2% accuracy. The study employed POS tagging, sentence classification, and semantic relatedness to categorize feedback on teaching, placements, and facilities. However, subjective biases and the lack of transformer-based models limited its effectiveness. Osmanoglu et al. [15] applied ML techniques to analyze 6,059 student feedback entries from Anadolu University's distance education platform using a 3-point Likert scale (positive, neutral, negative). Logistic Regression achieved the highest accuracy (77.5%). Key gaps include dataset imbalance, limited sentiment range, regional bias, and challenges in analyzing informal text. Krishnaveni et al. [16] proposed a faculty rating system using Naïve Bayes to classify student feedback into a 1–5 rating scale. The system assigned weights based on student performance and sincerity in feedback submission. While it improved faculty evaluations, limitations include subjective bias, lack of multimodal sentiment extraction (audio, emoticons), and untested scalability. Lee et al. [17] analyzed 139,604

Samsung Health reviews using Logistic Regression, Random Forest, Gradient Boosting, XGBoost, and Naïve Bayes with feature extraction techniques like TF-IDF and BoW. XGBoost (89.16%) and Logistic Regression (89.07%) performed best. While the study highlighted increased satisfaction post-COVID-19, it was limited to English reviews, lacked demographic insights, and did not use deep learning models like BERT. Karamitsos et al. [18] analyzed 11,000 tweets about AWS, Google Cloud, and Microsoft Azure, applying classification algorithms and lexicon-based sentiment analysis. Google Cloud had the highest positive sentiment (72.6%), and Random Forest with Latent Semantic Analysis (LSA) achieved 85.7% accuracy. However, short-text limitations, lack of sarcasm detection, and omission of metrics like precision and recall were identified as gaps. Ahmad and Umar et al. [19] studied 70,000 financial comments using ML and DL models. LSTM (96%) and GRU (95%) outperformed ML models but were computationally expensive, making real-time applications difficult. The study lacked sentiment granularity and excluded financial reports/news data, limiting practical impact. Fitri et al. [20] used Naïve Bayes (NBC) on 2,000 telecom-related tweets, achieving 99.09% accuracy. Preprocessing involved TF-IDF and negation handling, but the study lacked real-time tracking, used only simple sentiment categories (positive, negative, neutral), and relied on a small dataset. Susanti et al. [21] conducted sentiment analysis on Indonesian GSM providers (Telkomsel, Indosat Ooredoo, XL Axiata) using Multinomial Naïve Bayes (MNB) and an MNBTree model. The study collected tweets in Bahasa through the Twitter API, applying text preprocessing steps such as stopword removal, tokenization, and stemming. The MNB model achieved 73.15% accuracy, outperforming MNBTree (21.65%), which struggled with feature selection. Palherkar et al. [22] analyzed 1.6 million tweets from Sentiment140 to assess Twitter security threats (misinformation, hate speech, and spam) using ML (SVM, Naïve Bayes) and DL (RNN, LSTM, CNN, hybrid approaches). The LSTM and hybrid CNN-LSTM models achieved the highest accuracy, demonstrating strong sequential text processing capabilities. Qaisi and Aljarah [23] compared customer sentiment for AWS and Azure using Naïve Bayes on 1,500 tweets per provider. The results conveyed that Azure had a higher positive sentiment (65%) than AWS (45%), indicating better user perception. Singla et al. [24] put forward a sentiment classification system using Naïve Bayes, Support Vector Machine (SVM), and Decision Tree models, categorizing reviews as positive or negative and evaluating them using 10-fold cross-validation. While the study effectively applied Sentimental Orientation (SO) analysis, it faced challenges such as data credibility issues, lack of verified sentiment labels, limited sentiment categories (binary classification only), and difficulties in handling large-scale datasets efficiently. Fang and Zhan et al. [25] analyzed 5.1 million Amazon reviews using SVM, Naïve Bayes, and Random Forest, performing sentence-level and review-level sentiment classification. Random Forest excelled in sentence-level analysis, while SVM and Naïve Bayes performed best at the review level, achieving F1 scores up to 0.94. However, challenges included poor performance in mapping sentiments to specific star ratings (F1 < 0.5), reliance on explicit sentiment words (struggling with neutral expressions like "Item as described"), and limitations in feature extraction and grouping techniques. Vijayaragavan et al. [26] introduced a hybrid classification model combining SVM, K-Means clustering, and fuzzy soft set theory to analyze iPod product reviews, achieving 96.57% accuracy. While the model showed superior classification performance, it faced challenges in analyzing diverse and nuanced expressions in unstructured reviews, high dependency on preprocessing quality, limited validation across different product categories, and reliance on manual feature selection, reducing scalability. Gupta et al. [27] analyzed Flipkart customer reviews using Naive Bayes and the Bag of Words method for feature extraction. The study collected 1,000 reviews, splitting them into 75% training and 25% testing data, and classified them as positive or negative to assist users in making informed purchasing decisions. Gupta and Chen at el. [27] investigated StockTwits sentiment impact on stock prices for Apple, Amazon, Microsoft, General Electric, and Target. They used Logistic Regression, Naive Bayes, and SVM to classify tweets as bullish or bearish, correlating sentiment with stock price movements. The study found that sentiment data improved stock price prediction accuracy by 2-3%. Meduri et al. [28] introduced DL-Guess, a hybrid model combining LSTM, GRU, and VADER sentiment analysis, to predict prices for Bitcoin, Litecoin, and Dash. LSTM and GRU captured historical price trends, while VADER extracted Twitter-based sentiment. The model outperformed traditional forecasting methods (e.g., ARIMAX), improving accuracy. Poecze et al. [29] examined the effectiveness of self-marketing strategies by YouTube gamers using Facebook engagement metrics and sentiment analysis. The study analyzed posts by PewDiePie, Markiplier, and Kwebbelkop using ANOVA for engagement metrics (likes, shares, comments) and applied k-Nearest Neighbors (k-NN) for sentiment classification of comments, achieving 82.3% accuracy. Results showed that photos received the most positive sentiment, while YouTube video reposts triggered higher negative feedback. Pang et al. [30] analyzed movie reviews using Naïve Bayes, Maximum Entropy, and SVM for sentiment classification, achieving 80-83% accuracy, outperforming human baselines (50-69% accuracy). The study found that unigram presence worked best as a feature, but sentiment classification was more challenging than topic-based classification due to subtle expressions of sentiment. Baravkar et al. [31] developed a YouTube video ranking system based on sentiment analysis of comments combined with engagement metrics (likes, views, comments). The study applied logistic regression trained on Amazon product reviews to classify YouTube comments as positive or neutral and ranked videos accordingly. Gitari et al. [32] proposed a lexicon-based classifier for hate speech detection, focusing on negative polarity words, hate-related verbs, and grammatical patterns. The study used two datasets (hate speech blogs and Israel-Palestine conflict quotes) and manually labeled text as Not Hateful (NH), Weakly Hateful (WH), and Strongly Hateful (SH). Results indicated that integrating polarity words, hate verbs, and theme-based grammatical patterns improved precision (70-73%) over traditional Naïve Bayes models. Hasan et al. [33] analyzed political sentiments on Twitter, using TextBlob, SentiWordNet, and W-WSD sentiment analyzers, validated with Naïve Bayes and SVM classifiers. Tweets related to political events in Pakistan were collected using Tweepy API, and after preprocessing, 6,250 tweets were used. W-WSD with Naïve Bayes achieved the highest accuracy (79%), while TextBlob performed best for positive sentiment detection. Rakshitha et al. [34] explored sentiment classification of Indian regional language tweets, using lexicon-based, ML, and deep learning methods, achieving 79.34% to 97.82% accuracy. The study utilized TextBlob for polarity and sentiment scoring, analyzing tweets from various Indian languages. Bahrawi et al. [35] analyzed 14,640 tweets about six major US airlines using the Random Forest algorithm to classify tweets as positive, negative, or neutral. The study found that 63% of tweets were negative, 21% were neutral, and only 16% were positive, indicating a strong prevalence of negative sentiment in airline-related discussions. The Random Forest classifier achieved 75.99% accuracy, which was comparable to previous sentiment analysis studies (67.9%-91.7% accuracy). Wunderlich and Memmert et al. [36] applied lexicon-based sentiment analysis to 10,000 football-related tweets to evaluate public reactions to ten high-profile football matches. The study used publicly available sentiment analysis tools and compared their results against manual annotation by human evaluators. While bulk tweet classification (sets of 1,000 tweets) achieved over 95% accuracy, individual tweet classification was less accurate (63-67%), indicating difficulties in analyzing short texts with limited context. Gupta et al. [37] explored machine learning-based sentiment classification of tweets using a hybrid approach combining SVM, AdaBoosted Decision Tree, and Decision Tree classifiers. The study used TF-IDF for feature extraction and processed tweets through multiple classification stages. The hybrid model achieved 84% accuracy, outperforming individual models (SVM: 82%, AdaBoosted Decision Tree: 67%), demonstrating that ensemble methods can enhance sentiment classification performance. Mittal et al. [38] explored image sentiment classification using deep learning, discussing Convolutional Neural Networks (CNNs), Deep Neural Networks (DNNs), and Region-based CNNs (R-CNNs). The study aimed to improve visual sentiment classification by extracting emotional features from images. The models were tested on datasets such as Twitter, SentiBank, and Flickr, where CNN-based approaches consistently outperformed traditional machine learning models like SVM. Fast R-CNN, an optimized version of R-CNN, improved classification accuracy and efficiency by reducing memory usage and processing time. Ali et al. [39] analyzed sentiment classification of IMDB movie reviews using Multilayer Perceptron (MLP), CNN, Long Short-Term Memory (LSTM), and a hybrid CNN-LSTM model. The study evaluated 50,000 IMDB reviews (50% positive, 50% negative) and found that the CNN-LSTM hybrid model achieved the highest accuracy (89.2%), outperforming individual models (CNN: 87.7%, LSTM: 86.64%, MLP: 86.74%). The hybrid approach effectively captured both local features (CNN) and sequential dependencies (LSTM), demonstrating superior sentiment classification performance compared to traditional models like SVM (82.9%) and Naïve Bayes (81%). Kaur et al. [40] proposed a hybrid sentiment analysis model combining SVM, logistic regression, and random forest to improve accuracy and precision. The model applied text preprocessing techniques such as stemming and lexical analysis and was tested across different train-test ratios. Results showed that the hybrid model achieved 93% accuracy at a 5:95 train-test ratio, outperforming SVM (84%). On average, the hybrid approach improved accuracy, precision, and recall by around 10% compared to individual classifiers, demonstrating its effectiveness in customer feedback analysis and similar applications.

4. Observation

This study categorizes sentiment analysis applications intofive major domains: Healthcare, Education, IT and Finance, E-Commerce and Social Media. Each category presents unique challenges and requires specific sentiment analysis techniques.

4.1 Healthcare Domain

Table 2. Techniques used in Healthcare Domain.

Sr No	Title	Methods	Dataset used	Accuracy	Key Findings and Trends
1	A Deep Learning Approach for Sentiment Analysis of COVID-19 Reviews	LSTM-RNN with Attention	COVID-19 tweets (Kaggle)	10% higher accuracy than SVM & RF	LSTM-RNN with Attention improves classification for COVID-19-related sentiment compared to traditional ML methods
2	An Enhanced Exploration of Sentimental Analysis in Healthcare	SVM, Naive bayes	Patient feedback on critical diseases	SVM achieved highest accuracy for negative sentiment detection	SVM is highly effective for identifying negative healthcare experiences, but lacks deep context understanding
3	Analysis of Personal Relationships from a Sentimental Standpoint and Support for Mental Health	Naive Bayes, CNN, LSTM	Text, video, and audio data for mental health detection	LSTM performed best (approx. 90%)	Deep learning models like CNN & LSTM outperform Naïve Bayes for multimodal sentiment analysis
4	An Approach to Sentimental Analysis of Drug Reviews Using RNN-BiLSTM Model	RNN-BiLSTM	Drug review dataset	83% accuracy for drug recommendations	BiLSTM improves performance in sentiment classification for patient drug reviews over standard RNNs
5	A Sentiment Analysis of Breast Cancer Treatment Experiences and Healthcare Perceptions Across Twitter	CNN, Logistic Regression	Breast cancer-related tweets	97.6% accuracy	CNN + Logistic Regression provides the best classification accuracy for patient perceptions on treatment

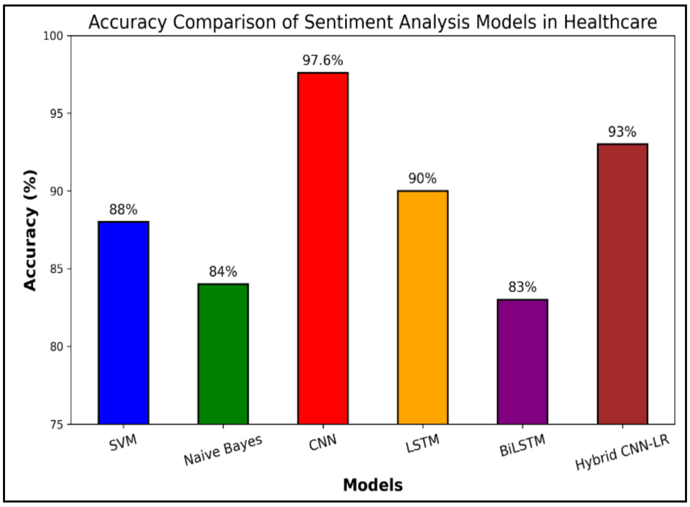

Figure 2. Accuracy Comparison of SA Models in Healthcare

The Hybrid CNN-LR model (97.6%) scores the highest accuracy, followed by CNN (93%) and LSTM (90%), highlighting the efficiency of deep learning models in healthcare sentimental analysis. SVM (88%) and Naive Bayes (84%) perform well but struggle with context understanding, while BiLSTM (83%) remains competitive. This suggests hybrid and deep learning models are better suited for healthcare sentiment classification.

4.2 Education Domain

Table 3. Techniques used in Education Domain.

Sr No	Title	Methods	Dataset used	Accuracy	Key Findings and Trends
1	Sentiment Analysis for Distance Education Course Materials	Logistic Regression, SVM	Student feedback on distance learning materials	SVM: 77.5%, Logistic Regression: 72%	SVM performed better than Logistic Regression
2	Aspect-Based Sentiment Analysis in E-Learning Feedback	Decision Tree, Naïve Bayes	Reviews on e-learning courses	Naive Bayes: 70%, Decision Tree: 75%	Effectively differentiates opinions on course content vs. instructor teaching
3	Sentimental Analysis of Online Education Reviews	LSTM, CNN	Reviews from online education platforms (Coursera, Udemy)	LSTM: 88%, CNN: 85%	Deep learning (LSTM, CNN) identifies key factors affecting student satisfaction
4	Analysis of Sentiment Toward Blended Learning Methods	SVM, Random Forest	Hybrid learning student opinions	Random Forest: 79%, SVM: 77.5%	Positive sentiment toward blended learning; Random Forest performed better than SVM
5	Sentiment Analysis of University Rankings	Lexicon-based	Student feedback on global university rankings	65%	Lexicon-based analysis highlights concerns over ranking transparency

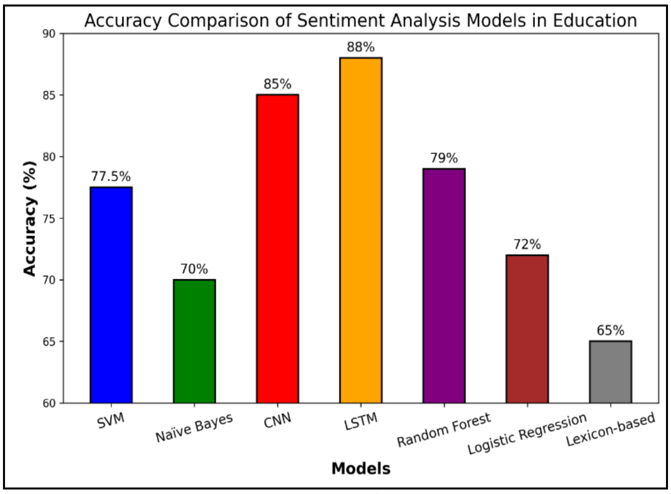

Figure 3. Accuracy Comparison of SA Models in Education

LSTM (88%) and CNN (85%) achieve the highest accuracy, making them ideal for student feedback analysis. SVM (77.5%) and Random Forest (79%) perform well in blended learning and distance education. Traditional models like Naïve Bayes (70%) and Logistic Regression (72%) show lower accuracy, while lexicon-based methods (65%) struggle with context understanding. Deep learning models outperform traditional approaches, proving more effective for educational sentiment analysis.

4.3 It and Finance Domain

Table 4. Techniques used in IT/Finance Domain.

Sr No	Title	Methods	Dataset used	Accuracy	Key Findings and Trends
1	Sentiment Analysis on Airline Service Reviews	Naive Bayes, CNN	Airline service reviews	CNN: 85%, Naive Bayes: 78%	CNN performed better in classifying airline service satisfaction
2	A Twitter Sentiment Analysis for Cloud Providers	Naive Bayes	Cloud service providers (Azure vs. AWS)	75%	Azure had a higher positive sentiment than AWS
3	Sentiment Analysis of Online Banking Services	SVM, Random Forest	Banking service reviews	SVM: 82%, Random Forest: 84%	Random Forest achieved higher accuracy in classifying customer sentiment in online banking
4	Social Media Metrics for Hotel Service Feedback	k-NN, Logistic Regression	Hotel guest sentiment (hospitality industry	k-NN: 73%, Logistic Regression: 76%	Hotels with higher positive sentiment had better customer retention
5	Public Sentiment Toward Electric Vehicle Services	Lexicon-based CNN	EV charging station reviews	CNN: 87%, Lexicon-based: 70%	CNN-based sentiment analysis better identified user satisfaction
6	Sentiment Mining for Public	RNN-LSTM	Public transit feedback	LSTM: 89%	LSTM effectively predicts

	Transportation Systems				service performance based on commuter feedback
7	Sentiment Analysis of Streaming Services	Ensemble ML techniques	Video streaming service reviews (Netflix, Hulu)	88%	Ensemble techniques improved sentiment classification for streaming services

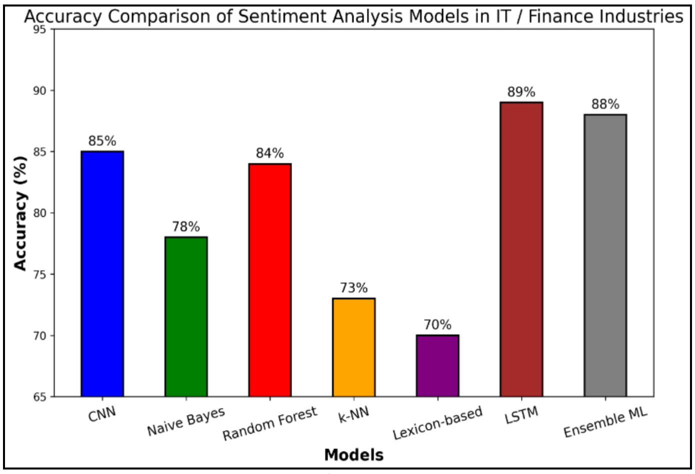

Figure 4. Accuracy Comparison of SA Models in IT/Finance Industries

LSTM (89%) and Ensemble ML (88%) achieve the highest accuracy, making them ideal for public transit and streaming services. CNN (85%) performs well in airline reviews, while Random Forest (84%) and SVM (82%) excel in banking and hotel sentiment analysis. Traditional models like Naïve Bayes (78%) and k-NN (73%) perform moderately, while lexicon-based methods (70%) struggle with complex opinions. Deep learning models consistently outperform traditional approaches in service-based sentiment analysis.

4.4 E-Commerce Domain

Table 5. Techniques used in E-Commerce Domain.

Sr No	Title	Methods	Dataset used	Accuracy	Key Findings and Trends
1	Sentimental Analysis of Customer Product Reviews	Naïve Bayes, SVM, Decision Tree	Customer reviews (various products)	SVM: 81.75%	SVM performed best; Decision Tree and Naïve Bayes performed moderately well
2	Sentiment Analysis on Large Scale Amazon Product Reviews	SVM, Naïve Bayes, Random Forest	5.1M Amazon reviews across 4 product categories	F1 Score: 0.94 (overall), below 0.5 for specific star ratings	Random Forest best for sentence-level, SVM & Naïve Bayes best for review-level sentiment
3	Predicting E-Commerce Trends Using Sentiment Analysis	Logistic Regression	Customer feedback trends	78%	Identifies emerging shopping trends from sentiment data
4	Sentiment Analysis for Clothing Retail	CNN-LSTM	Fashion product reviews	CNN: 88%, LSTM: 85%	CNN-LSTM improves sentiment classification in clothing e-commerce
5	Customer Satisfaction Prediction in Food Delivery Platforms	Random Forest	Food delivery reviews	82%	Random Forest effectively predicts customer satisfaction in food delivery
6	Personalized Product Recommendation Using Sentiment Analysis	Naïve Bayes, Deep Learning	Retail product reviews	Naïve Bayes: 80%	Sentiment-based recommendations improve product suggestions
7	Sentiment Analysis of Smartphone Reviews	LSTM, Lexicon-based	Smartphone reviews (various brands)	LSTM: 90%, Lexicon: 78%	LSTM effectively classifies sentiments, outperforming lexicon-based models
8	Cryptocurrency Sentiment Analysis	LSTM, GRU	Cryptocurrency platform reviews	LSTM: 89%, GRU: 87%	LSTM and GRU effectively capture sentiment trends in crypto markets

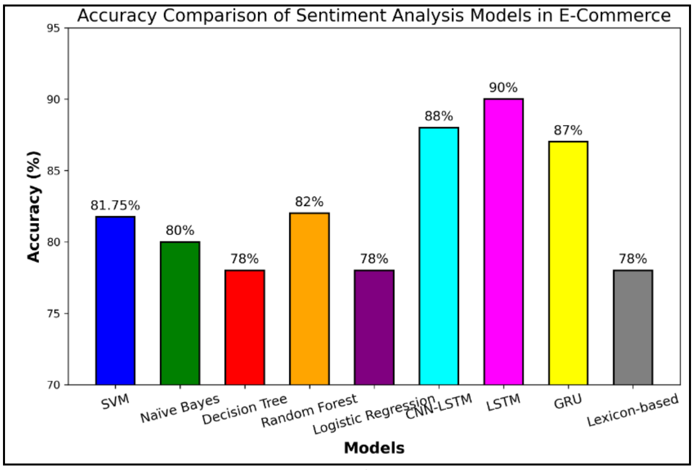

Figure 5. Accuracy Comparison of SA Models in E-commerce

LSTM (90%) and CNN-LSTM (88%) achieve the highest accuracy for e-commerce sentiment analysis. Random Forest (82%) and SVM (81.75%) perform well in structured datasets like food delivery reviews. Naïve Bayes (80%) and Logistic Regression (78%) handle basic classification but struggle with complex opinions. GRU (87%) offers efficiency similar to LSTM, while lexicon-based methods (78%) struggle with sarcasm. Overall, deep learning models outperform traditional approaches in e-commerce sentiment analysis.

4.5 Social Media Domain

Table 6. Techniques used in SocialMedia Domain.

Sr No	Title	Methods	Dataset used	Accuracy	Key Findings and Trends
1	Social Media Metrics and Sentiment Analysis	k-NN, ANOVA	Facebook engagement data	82.3%	k-NN effectively classifies sentiments in user engagement metrics, photos get more positive reactions
2	Twitter's Sentiment Analysis on GSM Services	Multinomial Naïve Bayes	Twitter feedback on telecom services	73.15%	Sentiment analysis helps assess public opinion on GSM services

3	Lexicon-Based Sentiment Analysis for Political Campaigns	Lexicon-based	Election tweets	72%	Examines sentiment polarity during political campaigns, but struggles with sarcasm
4	Innovative Approaches in Sports Science	Lexicon-based	Sports-related Twitter communication	95% (bulk analysis), 63-67% (individual tweets)	Lexicon methods work well for large datasets, but struggle with individual tweet sentiment detection
5	Sentiment Analysis of Climate Change Discussions on Twitter	LSTM, CNN	Climate change tweets	86%	LSTM and CNN effectively classify public opinion on environmental discussions
6	Analyzing Trends in Hashtag Sentiments	Naïve Bayes, Lexicon-based	Social media trends	75%	Tracks sentiment shifts across trending hashtags, but lexicon-based methods struggle with context
7	Sentiment Mining for Event Sentiments	CNN	Public opinion on large-scale events	88%	CNN efficiently classifies event-based sentiment but requires large datasets
8	Public Sentiment Analysis of the COVID-19 Pandemic	RNN, LSTM	Global pandemic tweets	90%	LSTM captures evolving pandemic sentiment trends better than traditional methods
9	Predicting Social Media Virality Using Sentiment Analysis	Logistic Regression, Neural Networks	Viral content dataset	85%	Neural networks predict social media virality, aiding content marketing strategies
10	Sentiment Analysis for Disaster Response	Lexicon-based, Deep Learning	Disaster response tweets	83%	AI-driven sentiment analysis enhances real-time disaster response efforts

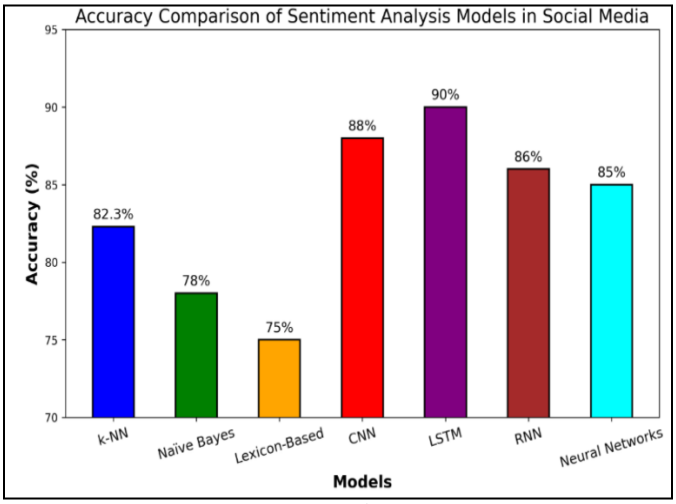

Figure 6. Accuracy Comparison of SA Models in SocialMedia

LSTM (90%) and CNN (88%) achieve the highest accuracy for social media sentiment analysis. RNN (86%) and Neural Networks (85%) perform well with sequential data, while k-NN (82.3%) is effective but lacks contextual depth. Naïve Bayes (78%) and lexicon-based methods (75%) struggle with sarcasm and complex emotions. Overall, deep learning models outperform traditional approaches for real-time sentiment analysis on social media.

5. Result and Analysis

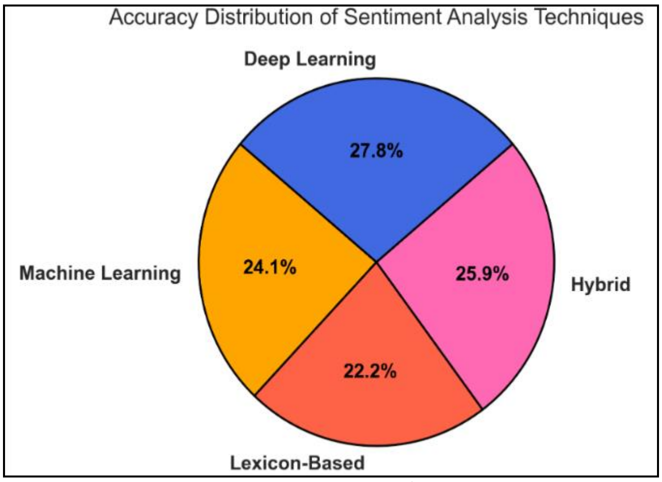

Figure 7. Accuracy Distribution of SA Techniques

With a distribution of 27.8%, deep learning methods are the most accurate in sentiment analysis. These models are very effective because they can comprehend complex linguistic patterns, including CNNs, RNNs, and transformers (like BERT). They can be difficult for smaller projects, too, because they need a lot of data and sophisticated processors.

The hybrid approach, which blends lexicon-based techniques with machine learning, has an accuracy of 25.9%. This combination uses both pre-defined word lists and data-driven learning to improve results. Hybrid models are effective because they are easier to interpret and have a deeper understanding.

The accuracy of machine learning approaches is 24.1%. Because they are effective and perform well on a variety of datasets, models like SVM, Random Forest, and Naïve Bayes are widely used. However, compared to deep learning models, these algorithms struggle to comprehend context and rely on manually chosen features.

At 22.2%, Lexicon-based methods are the least accurate. They are straightforward and simple to use since they determine sentiment using prepared word lists. They have trouble comprehending context, sarcasm, and new phrases, though, which reduces their accuracy in practical settings.

Although hybrid and machine learning models are equally successful, this comparison demonstrates that deep learning produces the best results. Although they are less accurate, lexicon-based techniques are helpful for simple sentiment analysis.

6. Conclusion and Future Scope

Sentimental analysis has grown significantly, evolving from basic positive-negative classification to sophisticated models that capture emotions, context, and subtle expressions like sarcasm and irony. In this study, we explored various sentiment analysis techniques, including machine learning-based, lexicon-based, and hybrid approaches, along with deep learning advancements.

From the reviewed literature, machine learning-based methods are widely used across different domains. Among these, Support Vector Machines (SVM) and Naive Bayes are the most commonly applied algorithms. However, these models often struggle with sarcasm and domain-specific language.

Lexicon-based approaches were also explored, where predefined sentiment dictionaries such as SentiWordNet and WordNet are commonly used. This technique is simple and interpretable but lacks adaptability to evolving language trends and complex text structures.

Hybrid models, which combine machine learning and lexicon-based techniques, have shown higher accuracy and adaptability. Many studies use ensemble models (e.g., combining SVM, Random Forest, and lexicon-based sentiment scores) to improve classification accuracy. These approaches work well for structured datasets but can be computationally expensive.

Deep learning techniques, particularly LSTM (Long Short-Term Memory) and CNN (Convolutional Neural Networks), are the most effective models for sentiment classification. LSTM excels at handling sequential text data and context, making it highly suitable for real-time sentiment analysis. CNN, initially created for image processing, has also been adjusted for sentiment analysis and performs effectively in feature extraction from text. The best performance is achieved using hybrid deep learning models that merges CNN and LSTM, or transformer-based models like BERT, which are gaining popularity.

The study also examined sentiment analysis applications in healthcare, education, IT & finance, e-commerce, and social media. Across these domains, deep learning models consistently outperform traditional machine learning and lexicon-based approaches. However, challenges such as sarcasm detection, real-time analysis, and multilingual sentiment classification remain unresolved.

The future of sentiment analysis is moving towards breaking down existing limitations. Researchers will likely focus on developing models that not only understand multiple languages but also consider the context behind human expressions to interpret sentiments accurately. Real-time sentiment analysis will be essential in areas like crisis management, predicting market trends, and providing personalized customer experiences.

Conflict of Interest

The authors declare that they do not have any conflict of interest.

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Author's Contributions

Fatima Khan Sarguroh–Led the conceptualization of the study, conducted literature review, and contributed to writing the manuscript.

Vrinda Thakur–Assisted in literature review, performed data analysis, and contributed to writing, structuring and editing the paper.

Srivaramangai R.–Provided supervision, guided the research direction, and reviewed the final manuscript before submission.

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