A Comprehensive Review of Sentiment Analysis: Concepts, Techniques, and Research Challenges

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ABSTRACT Sentiment analysis (SA) is a computational approach for analyzing large-scale textual data available on the Web in order to identify and classify subjective opinions expressed by users. The primary goal of sentiment analysis is to determine the polarity of opinions toward specific entities such as products, services, events, or topics, commonly categorized as positive, negative, or neutral. This paper presents a comprehensive review of sentiment analysis techniques, focusing on the methods used for sentiment extraction, classification, and polarity detection. Social networking platforms represent a rich and influential source of opinionated data, making sentiment analysis increasingly significant in areas such as business intelligence, political analysis, and public opinion assessment. The study surveys key research contributions in the field, covering both foundational approaches and recent developments up to 2017. The main objective is to provide a structured understanding of sentiment analysis concepts, classification strategies, and analytical methods. Furthermore, the paper discusses the integration of big data technologies with sentiment analysis, highlighting the role of Hadoop-based frameworks in efficiently collecting and processing large volumes of social media data for sentiment-driven applications.

Keywords Big data , Classification , Challenges , Sentiment analysis ,Social media , Twitter

1 INTRODUCTION

In recent years, the rapid expansion of the Internet and social networking platforms has enabled individuals to openly express their emotions, opinions, and experiences online. This extensive digital interaction has led to the generation of massive volumes of unstructured textual data. While such data are abundant, their practical value becomes evident only when they are systematically analyzed. Consequently, organizations, marketing agencies, and political campaigns increasingly rely on online opinion mining to determine whether public perceptions toward products, services, or events are positive, negative, or neutral [1], [2]. The growing volume of information exchanged over the Internet has driven the emergence of sentiment analysis (SA) as a significant research area. The concept of sentiment analysis was first introduced by Nasukawa [3] and later gained prominence within the domain of natural language processing (NLP) [4]. Sentiment analysis focuses on identifying and interpreting opinions, emotions, and attitudes expressed in textual content across social media platforms, review forums, and commercial websites. Commonly referred to as opinion mining, SA aims to classify text based on sentiment polarity, typically into positive, negative, or neutral categories [5]. Sentiment analysis has become an essential analytical tool for evaluating online reviews, surveys, and customer feedback. By analyzing user-generated content on ecommerce platforms, organizations can assess customer satisfaction, identify strengths and weaknesses of products, and make informed decisions to improve business performance [6]. Moreover, the rapid proliferation of diverse opinions on social networking sites has encouraged researchers, policymakers, psychologists, manufacturers, and decision-makers to develop intelligent systems capable of extracting meaningful insights from large-scale opinion data [7]. Recent advances in sentiment analysis have been significantly influenced by machine learning and deep learning techniques, which enable automated feature extraction and improved classification performance [8]. In particular, transformer-based models such as BERT and its variants have demonstrated superior contextual understanding and achieved state-of-the-art results in sentiment classification tasks [9], [10]. Furthermore, the integration of big data technologies has enhanced the scalability of sentiment analysis systems, enabling efficient processing of large-scale social media data using distributed frameworks such as Hadoop and Spark [11], [12]. These advancements continue to expand the applicability of sentiment analysis across multiple domains, reinforcing its importance as a core research area in data analytics and artificial intelligence. More recent studies have further explored advanced transformer-based frameworks, emphasizing scalability, robustness, and cross-domain adaptability in sentiment analysis applications [13].

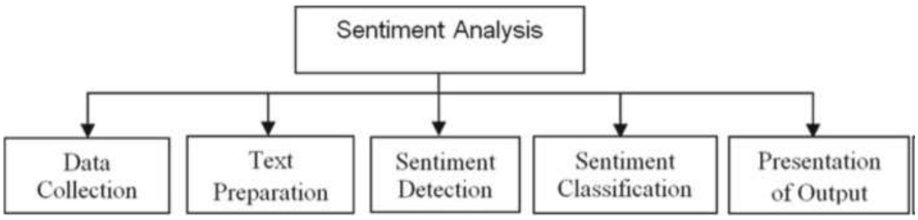

Fig 1. Sentiment Analysis process

2 Sentiment Analysis

In order to study the rapidly evolving opinions on social media and other platforms, sentiment analysis is becoming increasingly important. The enormous amount of information that has surged in recent years in communication sites, air traffic, and alternative markets cannot be controlled and analysed using the conventional methods, so scientists and researchers have developed high-efficiency techniques to deal with this data. In order to make the best choice, the Sentiment Analysis must digest the input and understand its polarity. Data collection, text preparation, sentiment detection, sentiment classification, and output presentation are the five processes in Sentiment Analysis data processing method as seen in Fig. 1.

2.1 Data Collection

Data collection is the first and most critical stage in the sentiment analysis process. It involves gathering opinionated textual data from multiple online sources such as social media platforms (e.g., Twitter, Facebook), review websites, blogs, forums, and news portals. The quality, diversity, and volume of collected data significantly influence the performance of sentiment analysis models [14]. In recent years, APIs and web scraping techniques have been widely used to collect large-scale datasets, while big data frameworks such as Hadoop and Spark enable efficient storage and handling of massive unstructured data [6]. Social media data is particularly valuable as it reflects real-time public opinions and emotions across various domains.

2.2 Text Preparation

Text preparation (also known as text preprocessing) transforms raw textual data into a clean and structured format suitable for analysis. This step typically includes tokenization, lowercasing, stop-word removal, stemming or lemmatization, handling emojis and hashtags, and removing noise such as URLs and special characters. Proper preprocessing reduces dimensionality and improves model efficiency and accuracy [12]. For social media data, preprocessing is particularly challenging due to informal language, abbreviations, and spelling variations, requiring specialized normalization techniques.

2.3 Sentiment Detection

Sentiment detection focuses on identifying subjective information within the text and determining whether a sentence or document expresses an opinion. This stage involves extracting sentiment-bearing words, phrases, or contextual representations using linguistic rules, sentiment lexicons, or feature extraction techniques [5]. Modern approaches rely heavily on word embeddings and contextual representations learned by deep learning models, which capture semantic relationships and contextual sentiment cues more effectively than traditional bag-of-words methods.

2.4 Sentiment Classification

Sentiment classification is the process of categorizing detected sentiment into predefined classes, typically positive, negative, or neutral. This task is performed using machine learning, deep learning, or hybrid approaches. Traditional classifiers such as Naïve Bayes and Support Vector Machines have been widely used, while recent advances favor deep learning architectures and transformer-based models such as BERT, which offer superior performance through contextual understanding [13]. Aspect-based sentiment classification further refines this process by assigning sentiment to specific attributes of an entity as shown in Fig 2.

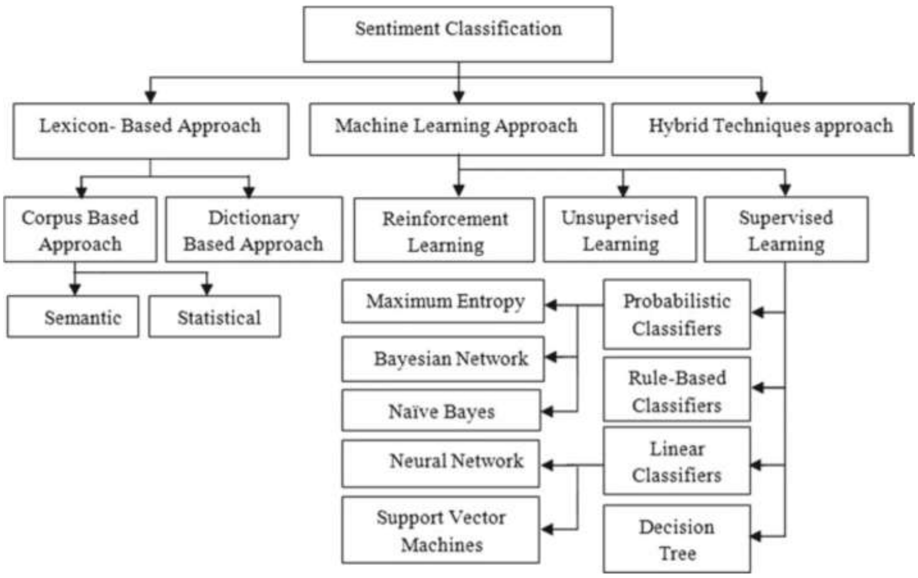

Fig 2 Sentiment classification techniques

2.4.1 Lexicon-Based Approach

The lexicon-based approach determines sentiment polarity by relying on predefined sentiment lexicons, where words are assigned sentiment orientations such as positive, negative, or neutral. This approach does not require labelled training data and is particularly effective for domain-independent sentiment analysis. However, its performance is sensitive to context, domain specificity, and linguistic phenomena such as negation and sarcasm [15][16].

2.4.1.1 Corpus based Approach

The corpus-based approach derives sentiment polarity from large textual corpora by analyzing word co-occurrence patterns and syntactic relationships. It adapts better to specific domains compared to dictionary-based methods. This approach often combines linguistic rules with statistical learning to infer sentiment orientation dynamically [17] [18].

2.4.1.A Semantic Approach

Semantic approaches focus on understanding the meaning and contextual relationships between words and phrases. These methods leverage ontologies, semantic networks, and contextual embeddings to capture deeper sentiment information beyond surface-level word polarity [21][22].

2.4.1.B Statistical Approach

Statistical approaches model sentiment using frequency-based features such as term frequency and n-grams. These approaches assume that sentiment patterns emerge statistically from large datasets and are often combined with probabilistic classifiers for improved accuracy [23][24]

2.4.3 Dictionary Based Approach

Dictionary-based sentiment analysis utilizes predefined sentiment dictionaries such as SentiWordNet or WordNet. Sentiment scores are computed by aggregating the polarity values of words appearing in the text. Although easy to implement, dictionary-based approaches often struggle with domain adaptation and evolving language usage [19] [20].

2.4.2 Machine Learning Approach

Machine learning-based sentiment classification treats sentiment analysis as a supervised or unsupervised learning problem. Models learn decision boundaries from features extracted from text data[25][26]. These approaches outperform lexicon-based methods when sufficient labeled data are available.

2.4.2.1 Reinforcement Learning

Reinforcement learning (RL) applies reward-based learning mechanisms to sentiment classification, enabling adaptive learning over time. RL is particularly useful in dynamic environments where sentiment patterns evolve continuously, such as social media streams[27][28].

2.4.2.2 Unsupervised Learning

Unsupervised learning techniques identify sentiment patterns without labeled data. Clustering and topic modelling methods are commonly used to discover latent sentiment structures in large corpora.[29][30]

2.4.2.3 Supervised Learning

Supervised learning relies on labelled datasets to train sentiment classifiers. These approaches typically achieve higher accuracy than unsupervised methods but require extensive annotation effort. [31][32]

2.4.2.3.a Probabilistic Classifiers:

They classify data using a variety of models. Mixture models come in a variety of forms, and each one needs to be an integrated mixture component. Every kind of this combo functions as a generator and might assist the specific

This method is known as a generative classifier.

i. Maximum Entropy Classifier: This type of classification is typically employed in NLP, voice, data, and problem-solving. For a number of natural language problems, including language modelling, part-of-speech tagging, and text segmentation, maximum entropy—also known as probability distribution estimation—is a significant and well-known method. The fundamental idea behind maximal entropy is the absence of outside knowledge.

2.4.2.3.b Maximum Entropy

Maximum Entropy models estimate sentiment probabilities by selecting distributions with the highest entropy under given constraints. These models are flexible and capable of incorporating diverse linguistic features, making them effective for sentiment classification tasks.[33][34]

2.4.2.3.c Bayesian Network

Bayesian Networks model probabilistic dependencies between sentiment features and classes. They are effective in handling uncertainty and integrating prior knowledge, though they may suffer from high computational complexity for large datasets.[35][36].

2.4.2.3.d Naive Bayes

Naïve Bayes classifiers are widely used in sentiment analysis due to their simplicity and efficiency. Despite their assumption of feature independence, they often achieve competitive performance on text classification tasks [37]

2.4.2.3.e Neural Network

Neural networks automatically learn hierarchical representations of text data. Deep architectures such as CNNs and LSTMs capture semantic and syntactic features, significantly improving sentiment classification accuracy [38].

2.4.2.3.f Support Vector Machines

Support Vector Machines (SVMs) construct optimal separating hyperplanes for sentiment classes. They are robust to high-dimensional feature spaces and have been extensively applied in early sentiment classification studies.[39][40].

2.4.2.3. Hybrid Techniques Approach

Hybrid approaches combine lexicon-based and machine learning techniques to leverage the strengths of both. These methods improve classification accuracy and domain adaptability by integrating rule-based sentiment scores with learned models.[41][42].

2.5. Presentation of output

The final stage of sentiment analysis involves presenting the classified sentiment results in a meaningful and interpretable chart, word clouds, or statistical summaries that support decision-making. Effective visualization helps stakeholders such as businesses, policymakers, and researchers quickly form. This may include sentiment scores, visual dashboards, interpret public opinion trends. In large-scale applications, sentiment outputs are often integrated into business intelligence systems or real-time monitoring platforms.

S.No	Approach	Technique	Learning Type	Strengths	Limitations	Typical Use Case
1	Lexicon-Based	Dictionary-Based	Unsupervised	No training data required, interpretable	Poor context handling, domain sensitivity	Small datasets, quick analysis
2	Lexicon-Based	Corpus-Based	Semi-supervised	Domain adaptability, improved polarity detection	Requires large corpora	Domain-specific sentiment
3	Statistical	Ontology / Embeddings	Unsupervised	Captures semantic relationships	High computational cost	Concept-level sentiment
4	Statistical	TF–IDF, N-grams	Supervised	Simple, efficient	Sparse features	Baseline sentiment models
5	Machine Learning	Naïve Bayes	Supervised	Fast, scalable	Independence assumption	Text-heavy datasets
6	Machine Learning	SVM	Supervised	High accuracy in high dimensions	Parameter tuning	Binary sentiment classification
7	Neural Networks	CNN / LSTM	Supervised	Automatic feature learning	Requires large datasets	Sentence/document sentiment
8	Transformer-Based	BERT, RoBERTa	Supervised	Context-aware, state-of-the-art	High resource usage	Fine-grained sentiment

9	Hybrid	Lexicon + ML	Hybrid	Improved robustness	Increased complexity	Cross-domain sentiment
10	Reinforcement Learning	Policy-based models	Adaptive	Dynamic learning	Complex training	Streaming sentiment data

Table 1. Comparison of Sentiment Classification Techniques

S. No	Technique	Accuracy	Precision	Recall	F1-Score	Computational Cost	Scalability
1	Dictionary-Based	Low–Medium	Medium	Low	Low	Very Low	High
2	Corpus-Based	Medium	Medium	Medium	Medium	Medium	Medium
3	Naïve Bayes	Medium	Medium	Medium	Medium	Low	High
4	SVM	High	High	Medium–High	High	Medium	Medium
5	Decision Tree	Medium	Medium	Medium	Medium	Low	Medium
6	Neural Networks (CNN/LSTM)	High	High	High	High	High	Medium
7	Transformer Models (BERT)	Very High	Very High	Very High	Very High	Very High	Low–Medium
8	Hybrid Models	High	High	High	High	Medium–High	Medium
9	Unsupervised (LDA, Clustering)	Low–Medium	Low	Medium	Low	Medium	High
10	Reinforcement Learning	Medium–High	Medium	High	Medium–High	High	Medium

Table 2. Mapping Sentiment Analysis Techniques to Performance Metrics

2.6 Discussion

The comparative analysis presented in Table I highlights the strengths and limitations of major sentiment classification techniques. Lexicon-based approaches remain attractive due to their simplicity and independence from labelled data; however, their inability to effectively capture contextual information and domain-specific sentiment limits their performance in complex real-world scenarios. Corpus-based and semantic approaches partially address these limitations by incorporating domain adaptation and semantic relationships, though they often require large datasets and higher computational resources.

Machine learning–based techniques, particularly supervised models such as Naïve Bayes and Support Vector Machines, demonstrate improved classification accuracy and robustness compared to purely lexicon-based methods, as summarized in Table 2. These models benefit from statistical learning of sentiment patterns and perform well in high-dimensional feature spaces. Nevertheless, their effectiveness is strongly dependent on the availability of labelled training data and carefully engineered features, which may not always be feasible in large-scale or multilingual environments.

Deep learning models, including CNNs and LSTMs, further enhance sentiment classification by automatically learning hierarchical feature representations from text. As shown in Table 2, these models consistently achieve higher accuracy, precision, recall, and F1-score values compared to traditional machine learning classifiers. However, their high computational cost and requirement for substantial training data pose challenges for real-time and resource-constrained applications. Transformer-based models such as BERT achieve state-of-the-art performance across nearly all evaluation metrics, including accuracy and F1-score, due to their ability to capture long-range contextual dependencies. Despite their superior performance, Table 2indicates that these models incur very high computational costs, which can limit scalability in large-scale sentiment analysis systems. Consequently, trade-offs between performance and efficiency must be carefully considered when selecting transformer-based approaches. Hybrid sentiment analysis techniques offer a balanced solution by combining lexicon-based knowledge with machine learning or deep learning models. As reflected in Tables I and 2, hybrid approaches achieve high performance while maintaining better adaptability across domains.

2.7 Challenges of Sentimental Analysis

Sentiment Analysis has gained significant attention in recent years due to its wide applicability in areas such as social media analytics, customer feedback mining, healthcare, and political opinion analysis. Despite notable advances in machine learning and deep learning models, sentiment analysis continues to face several unresolved challenges that affect its accuracy, generalizability, and interpretability.

1. Contextual and Semantic Ambiguity

One of the primary challenges in sentiment analysis is the context-dependent nature of language**.** Words may convey different sentiments depending on their surrounding context. For instance, a term that appears positive in isolation may express negativity in a sarcastic or comparative sentence. Traditional lexicon-based and bag-of-words approaches struggle to capture such semantic nuances, while even advanced neural models may fail in long or complex contextual dependencies.

2. Sarcasm, Irony, and Figurative Language

Sarcasm and irony significantly degrade sentiment classification performance, particularly in social media texts. Statements often express positive lexical cues while implying negative intent, making it difficult for automated systems to infer true sentiment. Detecting sarcasm requires pragmatic understanding, user intent modeling, and sometimes external knowledge, which remains an open research problem

3. Domain Dependency and Transferability

Sentiment polarity is highly domain-specific. Words such as *"unpredictable"* may be positive in movie reviews but negative in financial or medical contexts. Models trained on one domain often exhibit poor performance when applied to another due to domain shift. Domain adaptation and transfer learning methods partially address this issue, but achieving robust cross-domain sentiment analysis remains challenging.

4. Multilingual and Code-Mixed Text Processing

Most sentiment analysis systems are optimized for English, limiting their applicability to multilingual environments. Low-resource languages suffer from a lack of annotated datasets, sentiment lexicons, and pretrained models. Additionally**,** code-mixed text **(**e.g., mixing English and regional languages) introduces grammatical inconsistencies and lexical variations that significantly reduce classification accuracy.

5. Informal Language and Noisy Data

User-generated content often contains slang, abbreviations, emojis, misspellings, and grammatical errors. Such noisy data complicates preprocessing and feature extraction stages. Although emojis and emoticons convey sentiment cues, their interpretation varies across cultural and contextual boundaries, making reliable sentiment mapping difficult.

6. Imbalanced and Biased Datasets

Sentiment datasets frequently suffer from **class imbalance**, where neutral or positive samples dominate negative ones. This leads to biased models that favor majority classes. Moreover, data collection processes may introduce demographic or opinion bias, raising concerns about fairness and representational validity in sentiment prediction systems.

7. Aspect-Level and Fine-Grained Sentiment Analysis

While document-level sentiment analysis is relatively mature, aspect-based sentiment analysis (ABSA) **p**oses additional challenges. Identifying relevant aspects and associating correct sentiment polarity with each aspect within the same sentence requires advanced syntactic parsing and attention mechanisms. Handling conflicting sentiments within a single text remains a complex task.

8. Explainability and Model Interpretability

Deep learning models, particularly transformer-based architectures, achieve high accuracy but lack interpretability. In sensitive domains such as healthcare, finance, and governance, understanding why a particular sentiment decision is made is as important as the prediction itself. Developing explainable sentiment analysis models remains an ongoing research challenge.

9. Real-Time Processing and Scalability

Large-scale sentiment analysis applications require real-time processing of high-velocity data streams. Ensuring low latency, scalability, and robustness while maintaining accuracy is computationally expensive, especially for deep learning-based models.

2.8 Conclusions

In this paper, we present a survey and comparative analysis of current opinion mining methodologies, including lexicon-based and machine learning approaches, as well as cross-lingual and cross-domain techniques and some assessment metrics. According to research findings, machine learning techniques like SVM and naive Bayes are the most accurate and can be considered baseline learning techniques, although lexicon-based techniques are sometimes very successful and require little work in human-labeled documents. We also looked at how different features affected the classifier. We can draw the conclusion that more accurate results can be obtained with cleaner data. When compared to other models, the Bigram model offers superior sentiment accuracy. To increase the accuracy of sentiment classification and adaptability to a range of domains and languages, we can concentrate on the study of integrating machine learning methods with opinion lexicon methods.

Reference

[1] L. Zhang, S. Wang, and B. Liu, "Deep learning for sentiment analysis: A survey," *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, vol. 8, no. 4, p. e1253, 2018.

[2] A. Yadav and D. K. Vishwakarma, "Sentiment analysis using deep learning architectures: A review," *Artificial Intelligence Review*, vol. 53, pp. 4335–4385, 2020.

[3] T. Nasukawa and J. Yi, "Sentiment analysis: Capturing favorability using natural language processing," in *Proc. 2nd Int. Conf. Knowledge Capture*, 2003, pp. 70–77.

[4] W. Medhat, A. Hassan, and H. Korashy, "Sentiment analysis algorithms and applications: A survey," *Ain Shams Engineering Journal*, vol. 10, no. 4, pp. 1–13, 2019.

[5] E. Cambria, S. Poria, R. Bajpai, and B. Schuller, "Sentiment analysis beyond polarity: Recent advances and challenges," *IEEE Intelligent Systems*, vol. 33, no. 3, pp. 60–68, 2018.

[6] A. Kumar, T. M. Sebastian, and S. Gupta, "Sentiment analysis on social media data using machine learning and deep learning techniques," *Journal of Information and Optimization Sciences*, vol. 42, no. 2, pp. 351–364, 2021.

[7] H. Kaur, V. Mangat, and Nidhi, "A survey of sentiment analysis techniques," *International Journal of Computer Applications*, vol. 181, no. 2, pp. 1–6, 2018.

[8] M. H. Alam, W. J. Ryu, and S. Lee, "Joint multi-grain topic sentiment: Modeling semantic aspects for sentiment analysis," *Information Sciences*, vol. 528, pp. 204–218, 2020.

[9] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," in *Proc. NAACL-HLT*, 2019, pp. 4171–4186.

[10] A. Rogers, O. Kovaleva, and A. Rumshisky, "A primer in BERTology: What we know about how BERT works," *Transactions of the Association for Computational Linguistics*, vol. 8, pp. 842–866, 2020.

[11] E. Cambria, D. Hazarika, S. Poria, and A. Hussain, "Sentiment analysis and opinion mining: New perspectives," *Information Fusion*, vol. 89, pp. 1–14, 2023.

[12] S. Minaee, N. Kalchbrenner, E. Cambria, N. Nikzad, M. Chenaghlu, and J. Gao, “Deep learning–based text classification: A comprehensive review,” *ACM Computing Surveys*, vol. 55, no. 6, pp. 1–40, 2023.
[13] R. Sharma and P. K. Singh, “Transformer-based sentiment analysis: Recent trends and future directions,” *Expert Systems with Applications*, vol. 236, p. 121019, 2024.
[14] E. Cambria et al., “Sentiment analysis and opinion mining: New perspectives,” *Information Fusion*, 2023.
[15] B. Liu, *Sentiment Analysis and Opinion Mining*, Morgan & Claypool, 2012.
[16] T. Wilson, J. Wiebe, and P. Hoffmann, “Recognizing contextual polarity in phrase-level sentiment analysis,” *ACL*, 2005.
[17] P. Turney and M. Littman, “Measuring praise and criticism,” *ACM TOIS*, 2003.
[18] S. Mohammad et al., “Distributional semantics for sentiment analysis,” *ACL*, 2013.
[19] A. Esuli and F. Sebastiani, “SentiWordNet,” *LREC*, 2006.
[20] C. Strapparava and A. Valitutti, “WordNet-Affect,” *LREC*, 2004.
[21] E. Cambria et al., “SenticNet 6,” *Information Fusion*, 2020.
[22] J. Pennington, R. Socher, and C. Manning, “GloVe,” *EMNLP*, 2014.
[23] B. Pang, L. Lee, and S. Vaithyanathan, “Thumbs up?” *EMNLP*, 2002.
[24] C. Manning, P. Raghavan, and H. Schütze, *Introduction to Information Retrieval*, Cambridge Univ. Press, 2008.
[25] A. Yadav and D. K. Vishwakarma, “Sentiment analysis using ML architectures,” *AI Review*, 2020.
[26] S. Minaee et al., “Deep learning-based text classification,” *ACM Computing Surveys*, 2023.
[27] R. Sutton and A. Barto, *Reinforcement Learning: An Introduction*, MIT Press, 2018.
[28] J. Zhou et al., “Reinforcement learning for sentiment classification,” *Information Sciences*, 2021
[27] D. Blei et al., “Latent Dirichlet Allocation,” *JMLR*, 2003.
[28] S. Poria et al., “Unsupervised sentiment analysis,” *Knowledge-Based Systems*, 2016.
[29] J. Devlin et al., “BERT,” *NAACL-HLT*, 2019.
[30] R. Sharma and P. K. Singh, “Transformer-based sentiment analysis,” *Expert Systems with Applications*, 2024.
[31]Pang, Bo, Lillian Lee, and Shivakumar Vaithyanathan. *“Thumbs Up? Sentiment Classification Using Machine Learning Techniques.*
[32] Liu, Bing. *Sentiment Analysis and Opinion Mining.* Morgan & Claypool Publishers, 2012.
[33] A. Berger, S. Pietra, and V. Pietra, “A maximum entropy approach,” *Computational Lin guistics*, 1996.
[34] D. Jurafsky and J. Martin, *Speech and Language Processing*, Pearson, 2023.
[35] J. Pearl, *Probabilistic Reasoning in Intelligent Systems*, Morgan Kaufmann, 1988.
[36] M. H. Alam et al., “Probabilistic topic sentiment modeling,” *Information Sciences*, 2020.
[37] Y. Kim, “Convolutional neural networks for sentence classification,” *EMNLP*, 2014.
[38] S. Hochreiter and J. Schmidhuber, “Long short-term memory,” *Neural Computation*, 1997
[39] C. Cortes and V. Vapnik, “Support-vector networks,” *Machine Learning*, 1995.
[40] B. Pang and L. Lee, “Opinion mining and sentiment analysis,” *Foundations and Trends in IR*, 2008
[41] E. Cambria et al., “Hybrid sentiment analysis,” *Cognitive Computation*, 2017.
[42] R. Sharma and P. K. Singh, “Hybrid sentiment models,” *Expert Systems with Applications*, 2024.