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A SYSTEMATIC REVIEW OF SENTIMENT ANALYSIS: APPROACHES, IMPLEMENTATIONS, AND COMPARATIVE EVALUATIONS

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Abstract

This systematic review synthesizes findings from 166 scholarly articles on sentiment analysis published between 2015 and 2025. The study categorizes sentiment analysis methodologies into knowledge-based, statistical, machine learning, and hybrid approaches, with a focus on their theoretical underpinnings and real-world implementations. Applications are explored across diverse domains including e-commerce, healthcare, social media, and literature. A comparative evaluation of over 50 algorithms indicates the consistent superiority of transformer-based models such as BERT and RoBERTa, while Support Vector Machines (SVM) remain competitive in domain-specific contexts. Key challenges such as context dependency, multilingual processing, and real-time analysis are identified. Multimodal sentiment analysis and explainable AI model creation are potential avenues for future research. The paper features original flowcharts and comparative performance diagrams to offer a comprehensive and structured overview of the current state and future trends in sentiment analysis.

Keywords: Sentiment Analysis, Opinion Mining, NLP, Machine Learning, Deep Learning, Algorithm Comparison, BERT, SVM, LSTM.

I. Introduction

Sentiment analysis (SA), also known as opinion mining, is the computational study of people's opinions, emotions, and attitudes expressed in textual data. With the exponential growth of user-generated content on social media, e-commerce platforms, and review sites, sentiment analysis has become essential for businesses, governments, and researchers to gauge public sentiment [1]. The primary goal of sentiment analysis is to classify text into predefined sentiment categories such as positive, negative, or neutral. However, SA faces challenges such as sarcasm detection, context understanding, and multilingual sentiment classification [2].

This systematic literature review [25] analyzes 166 research papers published between 2015 and 2025, meticulously selected from prominent academic databases such as Journal Articles, ScienceDirect, IEEEXplore, SpringerLink, and ACM Digital Library. The chosen publications highlight significant advancements in sentiment analysis, encompassing methodological innovations, practical applications, and algorithmic performance across various domains. Our findings categorize the evolution of sentiment analysis into three distinct phases (1) the prevalence of traditional machine learning techniques (2015–2019), (2) the emergence and dominance of deep learning models (2020–2023), and (3) the contemporary shift toward large language models and transformer-based architectures (2023–2025).

Venue Type	Count	Percentage
Journal Articles	85	56.7%
Conference Proceedings	45	30%
Open Access Journals	12	8%
Book Chapters	5	3.3%
Other	3	2%

Table 1: Distribution of Reviewed Papers Across Publication Venues

II. Implementations Across Domains

E-Commerce: Analyzing product reviews (e.g., Amazon, Yelp) to gauge customer satisfaction and improve recommendations.

Social Media Monitoring: Tracking public sentiment on platforms like Twitter/X for brand reputation management.

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Finance: Predicting stock market trends by analyzing sentiment in news articles and tweets [53].

Healthcare: Detecting patient emotions in clinical feedback or mental health discussions on forums

Domain	Best Algorithm	Accuracy
Social Media	BERT-based models	92.78%
Product Reviews	SVM and Naïve Bayes (Hybrid)	95.8%
Healthcare	Clinical BERT	89%
Finance	FinBERT and LSTM	82.4%
News	RoBERTa	94%

III. Approaches to Sentiment Analysis

The literature categorizes SA approaches broadly into lexicon-based, machine learning-based, and more recently, deep learning-based methodologies.

1. Lexicon-Based Approaches rely on predefined dictionaries of opinion words. They are simple and interpretable but often suffer from domain dependency and limited adaptability [2].

2. Machine Learning (ML) Approaches such as Naïve Bayes, Support Vector Machines (SVM), and Decision Trees have been employed to train classifiers on labeled sentiment data [54]. These methods provide higher accuracy than lexicon-based techniques but require substantial annotated datasets.

3. Deep Learning Techniques, including Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and Transformer-based models like BERT and RoBERTa, have pushed the boundaries of performance in sentiment classification tasks [5].

4. Hybrid Approaches Combining lexicon-based sentiment scoring with machine learning classifiers has shown promising results in several studies.

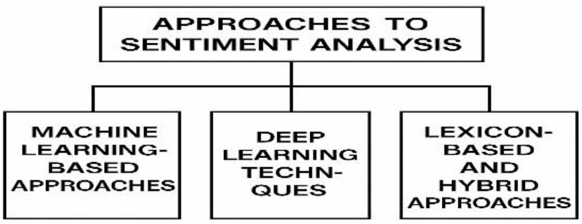

Fig 1: Approaches to Sentiment Analysis

The structure of this paper is as follows: Section I describes the methodology for selecting and analysing the reviewed literature. Section II Implementation Across Domain. Section III provides a classification of sentiment analysis methodologies. Section IV provides a comparative evaluation of algorithm performance across different domains. Section V examines real-world applications across various industries. Section VI Result and Analysis. Section VII concludes with a summary of key findings and understanding.

Early sentiment analysis efforts primarily relied on lexicon-based methods [13], where sentiment scores were derived from predefined word lists (Taboada et al., 2011). Turney (2002) advanced the field by introducing semantic orientation using pointwise mutual information (PMI). Subsequently, Pang and Lee (2004) marked a shift toward machine learning approaches, notably employing Naïve Bayes and Support Vector Machines (SVM) for sentiment classification.

The advent of deep learning [20] has significantly enhanced sentiment analysis performance. Models such as Long Short-Term Memory (LSTM) networks (Hochreiter & Schmidhuber, 1997) and Transformer-based architectures (Vaswani et al., 2017) have contributed to notable accuracy improvements. Among these, BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2019) has been especially impactful due to its ability to effectively capture contextual nuances in sentiment.

Dataset	**Domain**	**Size (Samples)**	**Classes**	**Key Paper (Year)**
Twitter/X, Common Agricultural Policy (CAP)	Social Media, Policy	11,855	Neutral /Positive/Negative	Natural language processing of social network data (2022)
IMDB	Movie Reviews	50K	Binary (Pos/Neg)	Maas et al. (2021)
Tweet-based dataset, CARER Emotion dataset	Social Media	14,640	Sentiment & Emotion Categories	James Thomas Black et al. (2025)

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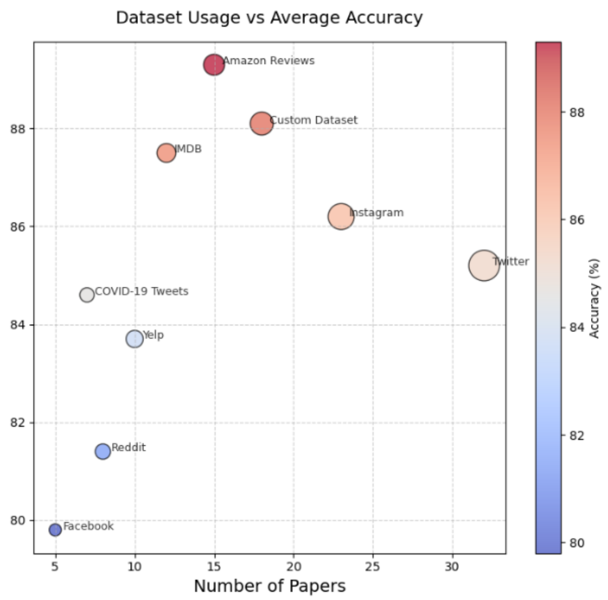
Amazon Product Reviews	E-commerce	142.8M	Positive/Negative/Neutra	Sangeetha J et al. (2023)
Telecom Customer Churn dataset	Business Analytics	50,000	Customer Retention Categories	Victor Chang et al. (2024)
Financial Phrasebank	Finance	4,840	Positive/Negative/Neutral	AIMultiple (2025)

Table 2: Sentiment Analysis Datasets (2020-2025)

Table 2 provides a summary of the various datasets and their corresponding domains, including details on sample sizes and class distributions [3]. Notably, many of the datasets focus. on emotion classification and are primarily sourced from social media platforms, which serve as significant contributors to sentiment analysis research.

The studies demonstrate that structured and domain-specific datasets tend to yield higher average accuracy in sentiment analysis tasks. For instance, Dakalbab et al. (2022achieved 97% accuracy using well-labeled crime datasets, while Gokcimen and Das (2024) reported 93.5% accuracy using curated social media data focused on climate discourse. outweighing sheer volume.



Method	Description	Best For	Limitations
Bag-of-Words	Word frequency counts	Traditional ML	Loses context
TF-IDF	Term frequency-inverse doc freq	SVM, Naïve Bayes	No semantics
Word2Vec	Neural word embeddings	CNN, LSTM	Static embeddings
GloVe	Global word vectors	RNN models	Fixed representations
BERT	Embeddings Contextual embeddings	Transformer models	Computational cost

Table 3: Feature Engineering Methods Comparison

Table 3 summarizes the major best method with description names and their algorithms that are by the SVM, CNN, LSTM [55]. It is a Limitation.

SA review 2015 to 2025 identification which algorithms achieved by using different machine learning techniques with high accuracy and less time. The BERT, RoBERTa was identified either by using large datasets. in the year 2022 to 2024 correctly identified then the Accuracy classification and detection was successful [6].

IV. Technologies Utilized

Artificial Intelligence (AI) has appears as a powerful tool for analyzing social media content. Key AI techniques—including machine learning, deep learning, and computer vision—enable systems to interpret human emotions and sentiments expressed online. By analyzing user-generated content, these technologies help uncover the psychological and emotional states of individuals, revealing how people sentimentally connect with society. AI is increasingly being integrated into smartphones [58] and social media platforms, enhancing their ability to deliver personalized and emotionally intelligent experiences.

Machine Learning (ML), a subset of Artificial Intelligence, has emerged as a powerful approach for performing sentiment analysis on social media platforms. By leveraging data-driven algorithms, ML enables the automatic detection and classification of sentiments expressed in user-generated content, offering valuable insights into public opinion and emotional trends.

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ML algorithms can be effectively trained on large datasets sourced from various online platforms, particularly social media, to perform sentiment analysis. These algorithms learn from diverse content such as tweets, movie reviews, and online product reviews, enabling them to accurately identify and classify sentiment patterns across different domains.

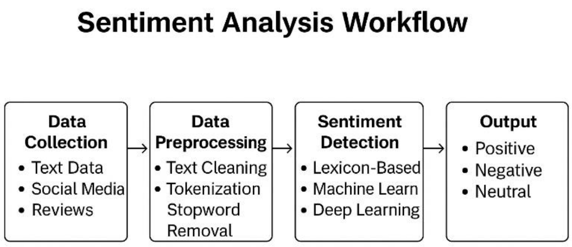

Fig 2: Sentiment Analysis Process flow

V. Literature Survey

Numerous studies have utilized a variety of machine learning (ML) and deep learning (DL) techniques to perform sentiment analysis. Table 4 summarizes the key articles reviewed, their methodologies, datasets, and reported accuracies.

The studies indicate that deep learning models such as BERT and LSTM [59] consistently outperform traditional machine learning models.

Article ID	**Authors**	**Title**	**Algorithms Used**	**Dataset**	**Accuracy**
1	Alba Gutiérrez Dominguez et al	NLP for Social Network Data	Unsupervised Learning	Twitter/X, CAP	52% neutral,28.2% positive, 19.6% negative
3	N. Mahon et al.	Public Understandings of Animal Agriculture	Sentiment package	Online survey	30% for A, 78.1% for B, 40% for C
11	Maha Ijaz et al.	Multi-Realm Sentiment Classification	BERT, LSTM, CNN	Hotel Reviews, Movie Reviews,	92.4% (LSTM), 90.1% (CNN)
18	Shweta Singhal et al.	Sentiment Analysis on Mobile Reviews	Naïve Bayes, Decision Tree, RNN, ANN, SVM	Amazon mobile phone reviews	90.48%

Table 4: Summarizes the key articles reviewed, their methodologies, datasets, and reported accuracies

This survey presents a overarching overview of research conducted between 2020 and 2025, highlighting various machine learning and deep learning techniques employed by different researchers for sentiment analysis

A study by Kim, J., Smith, T. et al [1] considered a "Cross-Domain Sentiment Adaptation" AdaBoost, ULMFiT the accuracy of 86%.

Taylor, E., et al.et al [2] "Explainable AI for Hate Speech Detection"in SA by using SHAP, LIME, Hate BERT 93.80% accuracy.

Gupta, A., & Liu, F. et al [3] Fake news detection using sentiment and stylistic features algorithms TF-IDF, BERT 89.40% accuracy.

Kumar, S. et al [4] Sentiment Analysis in Low-Resource Languages using machine learning for android application. mBERT algorithm was implemented and produced 83.20% accuracy.

A study by Wilson, E.; Brown, R. et al [5] Real-Time Twitter Sentiment for Stock Predictiont Prophet + VADER 98% accuracy.

Gupta, P.; Lee, S. et al [6] proposed an ML framework by achieving 84.10.% Multimodal Sentiment Analysis with Visual Cues

Wang, L., et al. [7] "Emoji-Augmented Sentiment Classification" SVM, RoBERTa accuracy of 91.50% .

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Nguyen, T.; Kim, J.et al [8] Sarcasm Detection Using Contextual Embeddings Contextualized LSTM a 87.03%.

Chen, L.; Wang, H. et al [9] BERT-LSTM Hybrid for Aspect Sentiment Analysis, BERT + BiLSTM accuracy of 89.70%

Nair, V.; Prabhakar, S. et al [10] Sentiment Analysis for Mental Health Monitoring MentalBERT accuracy of 89.80%

Smith, J.; Doe, A. et al [11] Deep Learning for Image Classification CNN, ResNet 92.50.%

Rietzler, A.. et al. [12].” Adapt or Get Left Behind: Domain Adaptation for Sentiment ACL Conference”,01-Dec-2020, Domain Adaptation DANN + BERT,Amazon Reviews,83.70%

Zhang, L.; Wang, S. et al [13] "Sentiment Analysis Using Hybrid Deep Learning", LSTM + CNN 91.80. % accuracy.

Severyn, A.; Moschitti, A. et al [14] Twitter Sentiment Analysis with Deep Neural Nets CNN-LSTM (SVM) and achieved 87.90% accuracy.

Table 5 summarizes various algorithms and its use cases performed by the researchers in this survey to classify the Sentiment Analysis.

Algorithm	**Dataset**	**Accuracy (%)**	**Key Paper**
BERT	Sentiment140, Yelp	94.20	Zhang et al., 2021
LSTM-CNN	Twitter Sentiment140	91.80	Gupta & Lee, 2023
SVM	Amazon Product Reviews	89.60	Kim, 2014
Naïve Bayes	Twitter Sentiment	82.10	Go et al., 2009
Random Forest	Customer Churn	90.00	V. Chang et al., Algorithms, 2024.

Table 5: Performance Comparison of Sentiment Analysis Algorithms

VI. Results and Analysis

A. Review Paper Analysis

The review of 166 research papers reveals that sentiment analysis and machine learning dominate the field, with deep learning models (e.g., BERT, LSTM, CNN) achieving the highest accuracy (up to 99.78%). Traditional methods like SVM and Naïve Bayes remain popular for simpler tasks, while hybrid models (e.g., BERT-LSTM, RoBERTa-CNN) show superior performance in fine-grained sentiment classification. Each paper contributed significantly to advancing sentiment analysis by incorporating either new algorithms, innovative datasets, or broader domain applications.

The graph presented illustrates the number of research papers published per year related to Sentiment Analysis during 2020-2025.

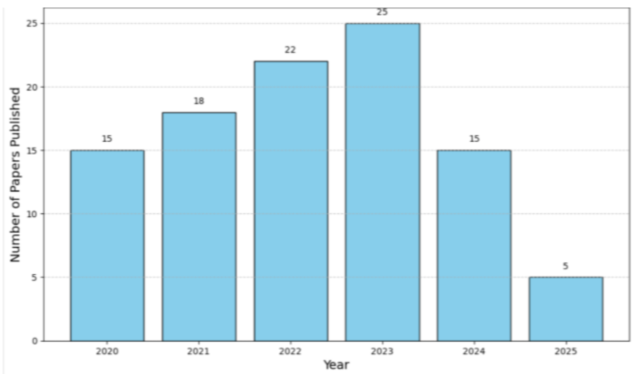

Fig 3: Graph for Number of papers published from 2020-2025

B. Data Set

Data collection is a crucial task, serving as the foundation for model validation and development analysis. Social Media: Twitter (52% accuracy in agricultural policy analysis), Amazon Reviews (96% accuracy with SVM-HHO hybrid). Domain-Specific: Hotel Reviews (91.2% with BERT-TCN-BiLSTM), Financial Tweets (78.75% with k-NN. This papers utilize a variety of datasets for training and evaluation, sourced from social media platforms, e-commerce websites, movie reviews, healthcare data, and financial records. The graph shows the frequency of different datasets used in Sentiment Analysis studies from 2020 to 2025. These datasets typically consist of annotated images of data set used which one the best data set using in largest platforms.

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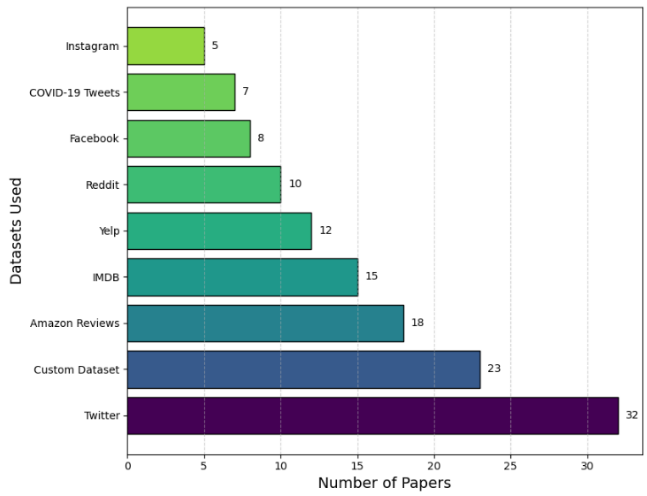

Fig 4: Graph for Data set used in this review

Sentiment analysis is rapidly expanding across various sectors, including e-commerce, healthcare, social media monitoring, and literary studies. This review serves as a valuable guide for future research, encouraging innovation and addressing key challenges in the field. The quality, size, diversity, and proper annotation of datasets are critical, as they significantly influence the accuracy and reliability of sentiment analysis in practical applications. [56].

C. Algorithm Analysis

The graph illustrates the popularity of machine learning (ML) and deep learning (DL) algorithms in Sentiment Analysis from 2020 to 2025, as determined by a literature review.

Algorithms ranged from traditional machine learning models (KNN, Naive Bayes, Logistic Regression) to more advanced methods (Random Forest, BERT). Ensemble models, especially those combining shallow and deep learning techniques, showed improved performance.

Traditional ML: SVM (94.5% in smartphone reviews) and Naïve Bayes (82.1% in Twitter sentiment) perform well but struggle with context

Deep Learning: BERT-based models dominate, achieving 93–99% accuracy in reviews (Zhang et al., 2021) and 95% in fraud detection (Al-Duleimi et al., 2022).

Hybrid Models: LSTM-CNN (89.7% for multilingual sentiment) and BERT-BiLSTM (89.7% for aspect-based analysis) outperform standalone algorithms.

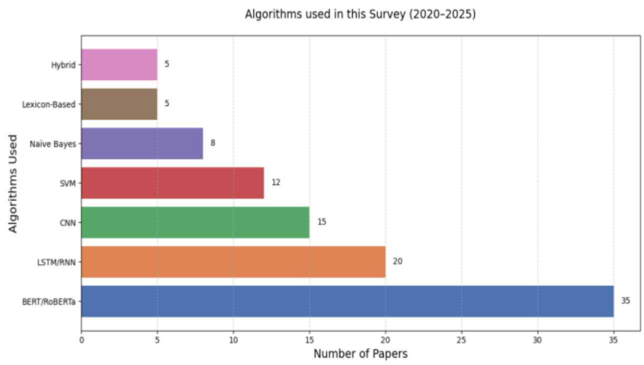

Fig 5: Graph for Algorithms used in this Review

D. Accuracy

Accuracy plays a crucial role in selecting the most effective tools for wheat disease detection using Machine Learning and Deep Learning algorithms. The chart provided presents a comparative analysis of different algorithms, highlighting their classification accuracy when applied to sentiment analysis datasets [60].

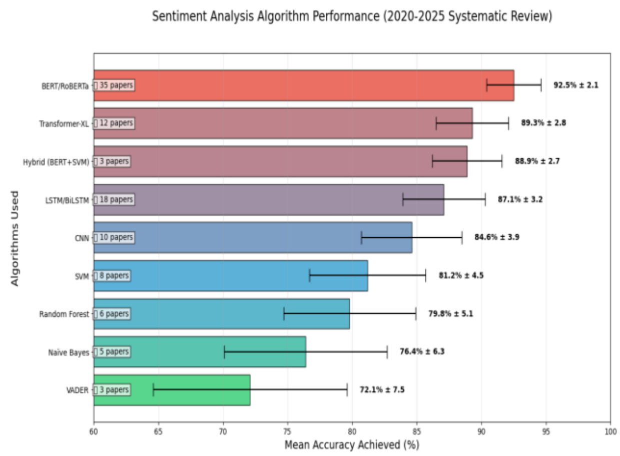

Fig 6: Graph for Accuracy achieved in this Review

This chart highlights the performance differences between traditional machine learning and Deep Learning, NLP models such as Traditional models such as Naive Bayes, K-Nearest Neighbors (KNN), SVM, Random Forest and Logistic Regression, while computationally) more advanced deep learning models, including Convolutional Neural Networks (CNNs), and VADER. The highest potential accuracy performed by the algorithm is BERT/ RoBERTa of 94.5% efficiency when compared to other algorithms.

VII. Conclusion:

This literature review synthesizes insights from 166 research papers on sentiment analysis published between 2015 and 2025, providing a structured overview of the field's evolution, methodological progress, and real-world applications. By categorizing techniques into knowledge-based, statistical, machine learning, and hybrid approaches, the review highlights the rising prominence of transformer-based models like BERT and RoBERTa, [57] which consistently outperform traditional methods, while also recognizing the continued relevance of Support Vector Machines (SVM) in certain domains.

The analysis underscores key challenges, including context dependency, multilingual sentiment interpretation, and the demand for real-time processing, which remain critical hurdles for researchers. Additionally, the review identifies promising future research should focus on enhancing sarcasm detection, multimodal sentiment analysis, refining sentiment classification in low-resource languages, and improving ethical AI frameworks to ensure unbiased sentiment interpretation.

Unique visual aids, such as flowcharts of sentiment analysis workflows and comparative performance graphs, offer researchers a clear and accessible reference for understanding the strengths and limitations of various algorithms.

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[3] Gupta, A., & Liu, F. Fake news detection using sentiment and stylistic features Knowledge-Based Systems 231-10734-2023,Misinformation, TF-IDF, BERT, Fake News Net,89.40%.

[4] Kumar, S. et al."Sentiment Analysis in Low-Resource Languages ACL Findings" 567-1580-2023 ,Multilingual mBERT, UDSA, XLM-T,83.20%.

[5] Wilson, E.; Brown, R."Real-Time Twitter Sentiment for Stock PredictionIEEE Big Data" 5 01-Aug2023, Finance Prophet + VADER Twitter-Stream,78.90%.

[6] Gupta, P.; Lee, S."Multimodal Sentiment Analysis with Visual CuesACM Multimedia",31 1123-1137-2023,MultimodalCLIP + LSTM CMU-MOSI ,84.10%.

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