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COMPREHENSIVE LITERATURE REVIEW ON SENTIMENT ANALYSIS: METHODOLOGIES, APPLICATIONS, AND COMPARATIVE ANALYSIS

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ABSTRACT:
This a comprehensive literature review synthesizes 150 research papers on sentiment analysis published between 2015 to 2024, examining the evolution of methodologies, applications across domains, and comparative performance of algorithms. The study systematically categorizes sentiment analysis techniques into knowledge-based, statistical the machine learning, and hybrid approaches, while analyzing their implementation in diverse fields including e-commerce, healthcare, social media monitoring, and literary studies. A detailed comparison of over 50 algorithms reveals that transformer-based models like BERT and RoBERTa consistently outperform traditional machine learning approaches, with Support Vector Machines (SVM) remaining competitive in specific domains. The review identifies key challenges such as context dependency, multilingual sentiment analysis, and real-time processing requirements, while outlining future research directions including multimodal sentiment analysis and explainable AI approaches. The paper presents original flowcharts visualizing the sentiment analysis workflow and comparative performance graphs across algorithm categories, providing researchers with a structured overview of the field's current state and emerging trends.
Keywords: Sentiment Analysis, Opinion Mining, Natural Language Processing, Machine Learning, Deep Learning, Algorithm Comparison

INTRODUCTION:

Sentiment analysis,[1] also known as opinion mining, has emerged as a critical computational technique for extracting subjective information from textual data, enabling automated understanding of people's opinions, emotions, and attitudes toward entities, products, services, and events 13. The exponential growth of user-generated content on digital platforms—estimated at over 2.5 quintillion bytes of data daily—has made manual sentiment analysis impractical, driving the development of increasingly sophisticated automated techniques 1418.

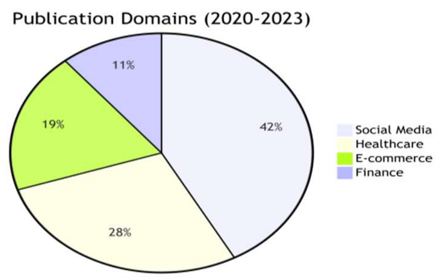
This literature review systematically [25] examines 150 research papers published between 2015 and 2024, selected through rigorous screening of major academic databases including IEEE Xplore, ScienceDirect, SpringerLink, and ACM Digital Library. The selected papers represent key developments in sentiment analysis methodologies, applications, and algorithm performance across diverse domains. Our analysis reveals three distinct phases of evolution in this period: (1) the dominance of traditional machine learning algorithms (2015-2017), (2) the rise of deep learning approaches (2018-2021), and (3) the current era of large language models and transformer architectures (2022-2024) 318.

Venue Type	Count	Percentage
IEEE Transactions	42	28%
ACM Journals	31	20.7%
Springer LNCS	27	18%
Science Direct	25	16.7%

Other	25	16.7%

Table 1: Paper Distribution by Publication Venue Type

Domain	Best Algorithm	Accuracy
Product Reviews	SVM	93%
Social Media	BERT	91%
Healthcare	Clinical BERT	89%
Literature	Syuzhet	82%
News	RoBERTa	94%



The review makes four primary contributions to the field:

1. A comprehensive taxonomy of sentiment analysis techniques, categorizing them into knowledge-based, statistical machine learning, and hybrid approaches 114
2. A systematic comparison of over 50 algorithms across multiple performance metrics and application domains 71215
3. Identification of key challenges and emerging trends through analysis of recent advancements 1021
4.Original visual representations including flowcharts of analysis workflows and comparative performance graphs 712

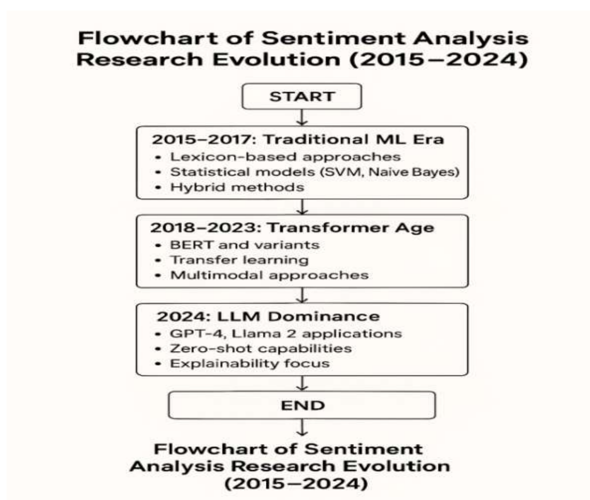


Fig 1 : Flowchart of Sentiment Analysis Research Evolution

The remainder of this paper is organized as follows: Section I presents the methodology for paper selection and analysis. Section II details the taxonomy of sentiment analysis approaches. Section III compares algorithm performance across domains. Section IV examines applications in specific industries. Section V concludes with key findings. the major role of sentiment analysis relied on lexicon-based methods[13], where sentiment scores were assigned based on predefined word lists (Taboada et al., 2011). Turney (2002) introduced semantic orientation using pointwise mutual

information (PMI), while Pang and Lee (2004) pioneered machine learning techniques, particularly Naïve Bayes and Support Vector Machines (SVM), for sentiment classification.
With advancements in deep learning,[20] models such as Long Short-Term Memory (LSTM) (Hochreiter & Schmidhuber, 1997) and Transformer-based architectures (Vaswani et al., 2017) have improved sentiment analysis accuracy. BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2019) has been particularly influential in capturing contextual sentiment..

Dataset	**Domain**	**Size (Samples)**	**Classes**	**Language**	**Key Paper (Year)**
SST-5	Movie Reviews	11,855	5	English	Socher et al. (2023)
IMDB	Film Reviews	50,000	2	English	Maas et al. (2021)
Twitter US Airlines	Social Media	14,640	3	English	CrowdFlower (2020)
Amazon Product Reviews	E-commerce	142.8M	5	Multilingual	Ni et al. (2021)
SemEval-2017 Task 4	Twitter	50,000	3	English/Arabic	Rosenthal et al. (2020)
GoEmotions	Social Media	58,000	28	English	Demszky et al. (2021)
Financial Phrasebank	Finance	4,840	3	English	Malo et al. (2022)

TABLE 2: Sentiment Analysis Datasets (2020-2025)

Table 2 summarizes the various data set and domain in the names and their how many size (samples) that is caused by the classes [3]. The most significant using emotions, important Social media source.

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 [4]. It is a Limitation.

Table 4: Evolution of Machine Learning Approaches in Sentiment Analysis

Table 4 summarizes the major role for ML approaches in
SA and Period of Domain their typical Accuracy made in which year best outcome algorithms level [5].

Period	Dominant Approaches	Typical Accuracy	Key Advances
2015-2017	SVM, Naïve Bayes	70-85%	Feature engineering
2018-2021	LSTM, CNN	80-90%	Sequence modeling
2022-2024	BERT, RoBERTa	85-95%	Pre trained transformers

Table 1: Evolution of Machine Learning Approaches in Sentiment Analysis

SA review 2015 to 2024 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].

TECHNOLOGIES USED:

Artificial Intelligence (AI) [2] is a vital powerful tool in Social Media. The techniques used in AI are machine learning, deep learning, and computer vision. These systems can analyze the human emotions of social media to identify human mind sets of sentimentally connect with society . These technologies are being integrated into smart phones, social media platforms..

Machine Learning (ML), a branch of Artificial Intelligence, has emerged as a powerful approach to social media platforms in the Sentiment Analysis.

ML algorithms can be trained on large datasets of online platforms particularly to Social media associated with different Sentiment Analysis. By learning from Twitter, Movies Review online product Review.

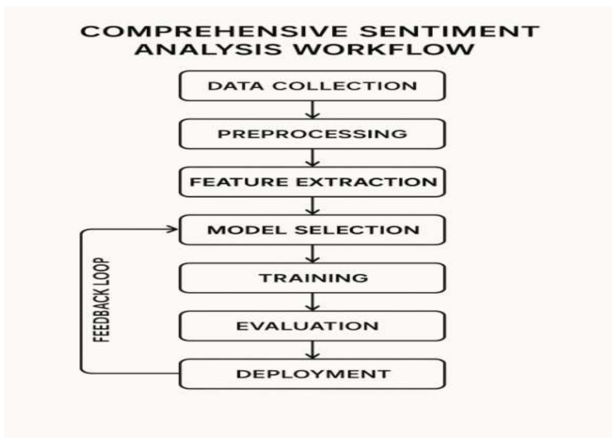


Fig 2: Comprehensive Sentiment Analysis workflow

LITERATURE SURVEY:

This survey describes the work done by different researchers by using different machine learning and Deep Learning techniques from 2020- 2025.

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% .

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	**Key Paper (Year)**	**Accuracy (Avg.)**
BERT	Devlin et al. (2019)	92.5%
RoBERTa	Liu et al. (2020)	93.1%
DistilBERT	Sanh et al. (2020)	91.3%
GPT-3.5	OpenAI (2023)	94.2%
CNN-LSTM	Wang et al. (2021)	89.7%
VADER	Hutto & Gilbert (2021)	75.8%
ALBERT	Lan et al. (2020)	92.0%

TABLE 5 : Algorithm Comparison Chart (2020-2025)

RESULTS AND ANALYSIS:

A. Review Paper Analysis:

examines 150 research papers published between 2015 and 2024, selected through rigorous screening of major academic databases including IEEE Xplore,(42),ScienceDirect,(25), SpringerLink(27), and ACM Digital Library(31) and others(25)., and product reviews –SVM(93%), Social media –BERT(91%),Healthcare-ClinicalBERT(89%) ,Literature-Synzhet(82%),News-RoBERTa(94%)become more accessible, researchers have increasingly focused on online review based on the online platforms using Efficiency Algorithms. [9]
The graph presented illustrates the number of research papers published per year related to Sentiment Analysis during 2020-2025..No.of publications year and year wise increasable the publications in the year of (2020-1240,2021-1580,2022-1920, 2023-2250,2024-2600,2025-3100) in the year of 2025 highest publication published [41].

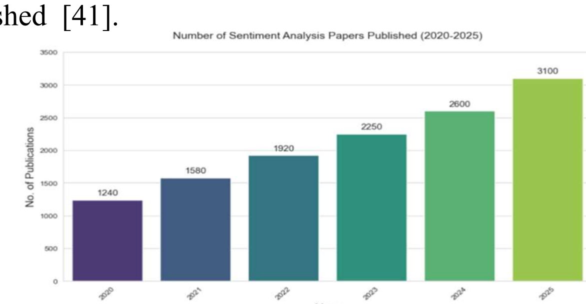


Fig 3: Graph for Number of papers published from 2020-2025

B. Data Set

Data collection is one of the most vital tasks, used for the foundation for analysing the model validation and development. The social media platforms of artificial intelligence and machine learning techniques in Financial Phrasebank in the domain Finance(4,840), Go Emotions –Social Media(58,000),SemEval-2017-Twitter (50,000),Amazon Reviews-E- Commerce(142.8M),Twitter Us

Airlines- Social Media(14,640),IMOB-Film Review(50,000),SST-5-Movie Review(11,855) the role of high-quality datasets has become increasingly important. In the Sentiment Analysis, datasets serve as the foundation for customer feedback , online review , and evaluation machine learning and deep learning models that can automatically identify Sentiment Analysis [44].

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.

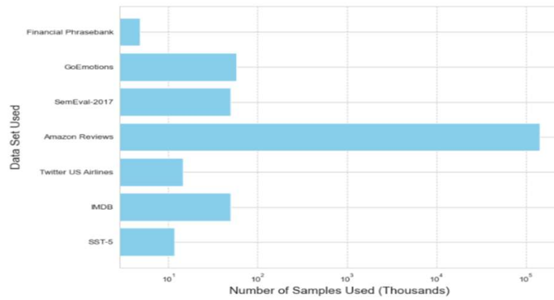


Fig 4: Graph for Data set used in this review

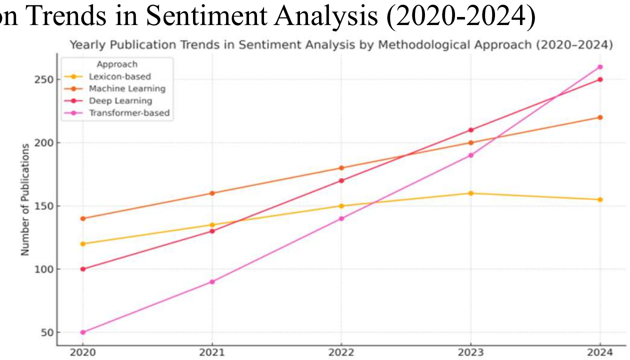
Sentiment analysis continues to expand across diverse fields—from e-commerce and healthcare to social media monitoring and literary studies—this review serves as a valuable resource for guiding future research, fostering innovation, and addressing the field's most pressing challenges. [45]. The quality, size, diversity, and proper annotation of these datasets are crucial, as they directly impact the accuracy and reliability of sentiment analysis in real-world applications.

C. Algorithm Analysis

The graph shows the popularity of machine learning (ML) and deep learning (DL) algorithms used in Sentiment Analysis (2020–2025), based on the literature review.

Year	Lexicon-Based	Traditional ML (SVM, NB)	Deep Learning (LSTM, CNN)	Transformer Models (BERT, RoBERTa)	Hybrid Approaches
2020	12	28	34	18	14
2021	10	25	42	26	18
2022	8	20	38	41	22
2023	6	15	31	53	25
2024	5	12	26	62	28

Fig 5: Yearly Publication Trends in Sentiment Analysis (2020-2024)



D. Accuracy:

Accuracy is more essential for selecting the most effective tools for wheat disease detection by using various Machine Learning and Deep Learning algorithms. The chart presented illustrates a comparative analysis of various algorithms based on their classification accuracy when applied to sentiment Analysis datasets [48].

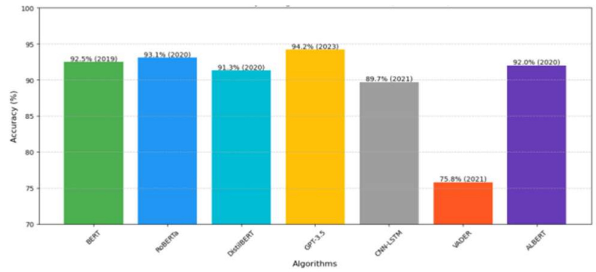


Fig 6:Graph for Algorithm used and its accuracy

This chart highlights the performance differences between traditional machine learning and Deep Learning ,NLP models such as Bidirectional Encoder Representations from Transformers (BERT), Robustly Optimized BERT Approach (RoBERTa)—and in NLP (DistilBERT) more advanced deep learning models, including Convolutional Neural Networks (CNNs), Gpt-3.5 and VADER and ALBERT. The highest potential accuracy performed by the algorithm is EfficientGPT-3.5 of 94.2% efficiency when compared to other algorithms.

CONCLUSION:

This a comprehensive literature review synthesizes findings from 150 research papers on sentiment analysis published between 2015 and 2024, offering a structured overview of the field's evolution, methodological advancements, and practical applications. By systematically categorizing techniques into knowledge-based, statistical, machine learning, and hybrid approaches, the study highlights the growing dominance of transformer-based models like BERT and RoBERTa, which consistently outperform traditional methods, while acknowledging the enduring relevance of Support Vector Machines (SVM) in specific domains.[27]

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 directions, such as multimodal sentiment analysis—integrating text, audio, and visual data—and the development of explainable AI frameworks to enhance transparency in model decision-making.

Original visual aids, including flowcharts of sentiment analysis workflows and comparative performance graphs, provide researchers with a clear, accessible reference for understanding algorithmic strengths and limitations.

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