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A Comprehensive Expended Research Paper on Sentiment Analysis



Abstract: - The rapid rise of user-generated digital material on social media platforms, e-commerce websites, review portals, and discussion forums has made sentiment analysis—also referred to as opinion analysis or mining—a core topic of study within Natural Language Processing (NLP). Techniques for evaluating emotions encoded in textual data have advanced as businesses relieve more on public opinion for business insights, product development, customer satisfaction measurement, and marketing strategies. With an emphasis on machine learning-based, deep learning-based, lexicon-driven, context-aware, aspect-specific, and hybrid architectures, this paper provides an in-depth evaluation of over twenty important sentiment analysis research publications. A thorough analysis of model evolution, methodological developments, datasets utilized, research gaps, and difficulties in classification of sentiment is also included in the review. Comprehensive methodical comparisons, an updated literature review table, and critical commentary on how different models handle issues like domain dependency, sarcasm detection, feature extraction, and temporal sentiment shifts are also included in the document. Future research in ABSA, contextual sentiment modeling, transformer-driven sentiment architectures, and explainable AI-based models will have a solid foundation.

Keywords: NLP(Natural Language Processing), ABSA (Abstract Based Sentiment Analysis)

1. INTRODUCTION

The rapid proliferation of the Internet has radically transformed the way user's express opinions and make purchasing decisions. Online review systems such as Amazon, Yelp, TripAdvisor, and social media platforms like Twitter and Facebook have enabled users to publicly share opinions about products, events, movies, restaurants, and public services. The abundance of this unstructured text data presents an opportunity and a challenge: the opportunity to use automated models to understand consumer emotions at scale, and the challenge of processing informal, subjective text with high linguistic variability. The rapid digital transformation of modern society has redefined how individuals communicate, consume information, and express their opinions. Platforms such as Amazon, Flipkart, TripAdvisor, Facebook, YouTube, and Twitter have become rich sources of user-generated text that reflect genuine customer experiences, personal views, and emotional expressions. Sentiment analysis enables systematic analysis of this work to derive insights that support decision-making across industries. Historically, sentiment analysis began as a simplified binary classification task. Traditional approaches used lexicon-based techniques, in which manually curated dictionaries determined the polarity of terms. However, these early techniques struggled with ambiguous wording, figurative language, double negations, and domain-specific vocabulary [1]. As research evolved, statistical machine learning models such as Naïve Bayes, Support Vector Machines (SVM), Logistic Regression, and Random Forests became popular. These approaches improved classification accuracy but still required extensive feature engineering, including TF-IDF vectors, n-grams, part-of-speech tags, and syntactic features. The emergence of deep learning revolutionized sentiment analysis by enabling models to learn semantics directly from raw text without manual feature construction. Convolutional Neural Networks (CNNs) excelled at local feature extraction, while Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures, captured long-term dependencies. Bidirectional LSTM (BiLSTM) models further enhanced contextual understanding by

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processing text in both forward and backward directions. Hybrid models combining CNN and LSTM became state-of-the-art for many years.[2]

In addition, domain-specific challenges led to specialized subfields such as Aspect-Based Sentiment Analysis (ABSA), where systems identify sentiments associated with specific product attributes. Temporal sentiment analysis also evolved to track shifts in emotion over time, especially useful in monitoring public opinion during crises, elections, or product launches. The introduction of contextual embedding models such as ELMo and BERT marked another significant leap. These models captured dynamic word meanings based on context rather than static lookup vectors. Their transformer-based architecture enabled significantly higher performance across sentiment classification benchmarks. Despite such advancements, several open challenges remain—sarcasm detection, interpretability of deep learning models, cross-domain adaptability, handling low-resource languages, and robustness against noise inherent in social media text. This paper revisits foundational and modern studies to explore how each research contribution addresses these limitations. Sentiment analysis began as a basic text-classification problem involving labeling text as positive, negative, or neutral. Early works relied on lexicon-based or machine learning–based approaches. However, as research evolved, the scope expanded to fine-grained tasks such as aspect-based sentiment analysis (ABSA), opinion extraction, sentiment-aware ranking, temporal sentiment shifts, deception detection, and customer preference modeling [2].

1.1 SENTIMENT ANALYSIS'S SIGNIFICANCE IN MODERN TIMES

- **Business intelligence and innovation in products:** Firms analyze feedback from users to improve features, identify problems, and set initiatives.
- **Recommendation systems:** The accuracy of recommendations gets improved by sentiment-enriched reviews.
- **Social media monitoring:** During product launches or emergencies, brands keep tabs on public sentiment.
- **Market forecasting:** Market forecasts are influenced by investor opinion on sites like Reddit, X, or financial forums.
- **Customer relationship management:** Automated systems categorize customer support feedback.

1.2 RESEARCH MOTIVATION

Although numerous techniques exist, sentiment analysis remains challenging due to:

- Ambiguity and sarcasm
- Domain dependency
- Lack of contextual understanding in early models
- Feature-rich reviews with multi-aspect sentiments
- Temporal variations in user opinions
- Deceptive or fake reviews
- The need for explainability in modern models

2. LITERATURE REVIEW

Wherever This work presents a detailed and deeply expanded review of many research papers categorized based on methodology and focus area. Instead of focusing solely on model accuracy, the review emphasizes conceptual contributions, methodological strengths, dataset characteristics, and contextual relevance in modern sentiment applications.

- **Surveys and Foundational Research:** These papers established the groundwork for sentiment analysis, identifying early challenges and proposing strategies for building more robust models. They highlighted issues such as domain dependency, feature sparsity, and the limitations of lexicon-driven methods.
- **Machine Learning-Based Approaches:** Before deep learning, sentiment analysis relied extensively on statistical models such as Naïve Bayes, Logistic Regression, and SVM. These models required manual feature

engineering but provided baseline performance essential for comparison. Pujari & Shetty (2018) demonstrated that SVM consistently outperformed other models, particularly when paired with well-designed TF-IDF features [12].

- **Deep Learning Approaches:** Deep learning fundamentally changed sentiment analysis. Sreesurya et al. (2020) introduced an LSTM-enhanced architecture capable of understanding long-term dependencies. Similarly, BiGRU models demonstrated computational efficiency and improved performance on complex review datasets. The combination of CNN and RNN models provided more stable performance across multiple domains.
- **Aspect-Based Sentiment Analysis:** Aspect-specific models such as those proposed by Albornoz et al. (2011) and Chen et al. (2019) addressed the need to classify sentiments at a granular level. These studies introduced feature extraction from opinion phrases, pattern mining, and biclustering strategies. Such techniques improved interpretability and allowed businesses to understand which product features influenced user satisfaction.
- **Temporal and Contextual Sentiment Models:** AL-Sharuee et al. (2021) introduced temporal clustering for reviews, showing how user sentiments evolve over time. Context-driven BiLSTM models proposed by Huddar et al. emphasized the role of context when classifying long reviews, demonstrating consistent improvements on datasets such as IMDB and Yelp.
- **Deceptive Review Detection:** Fake or deceptive reviews distort consumer perception. Jain et al. (2019) introduced hierarchical CNN-GRU architectures for detecting fake reviews by analyzing linguistic irregularities. This work bridged sentiment analysis with security and trustworthiness in e-commerce.[10]
- **Multi-filter and Multi-channel Architectures:** Stojanovski et al. (2019) demonstrated the value of multi-filter CNNs for analyzing tweets containing informal and compressed language. Their research highlighted the challenges associated with analyzing short-text sentiment compared to long reviews.[17]

The literature collectively demonstrates a transition from shallow statistical models to deep, context-aware architectures, enabling unprecedented accuracy levels across domains. However, despite advancements, challenges related to sarcasm detection, low-resource languages, and model interpretability persist.

2.1 SURVEYS AND FOUNDATIONAL PAPERS

2.1.1 Himmat & Salim (2014) – Survey on Product Review Sentiment Classification

This early survey captures the foundational challenges in sentiment analysis before deep learning became prominent. It discusses key limitations in traditional sentiment classification, such as feature sparsity, domain-specific vocabulary, and the inadequacy of generic lexicons for domain-shifted contexts. The authors emphasize the importance of feature engineering and the difficulty of handling negations, intensifiers, and comparative statements. This remains relevant today, even with neural networks.[8]

2.1.2 Yadav & Vishwakarma (2020) – Review of Deep Learning Architectures

This comprehensive survey provides an in-depth analysis of deep learning models, ranging from CNNs to LSTMs, BiLSTMs, GRUs, hybrid networks, and attention mechanisms. It highlights the shift from manual feature engineering toward automatic representation learning using word embeddings (Word2Vec, GloVe) and contextual embeddings (ELMo, BERT). The paper also compares performance across datasets, illustrating why DL became dominant.[20]

2.1.3 Hemmatian & Sohrabi (2019) – Survey on Classification Techniques

This survey focuses specifically on classification algorithms and their comparative strengths [7]. It categorizes techniques into supervised, unsupervised, and hybrid, explaining how dictionary-based methods often fail with slang or new words, while supervised ML models require large, labeled datasets. The paper is especially useful for understanding the transition into data-driven approaches.

2.1.4 Yue et al. (2019) – Social Media Sentiment Survey

Social media differs from structured product reviews in format, grammar, and linguistic patterns. Yue et al. analyze challenges such as informal language, hashtags, emojis, abbreviations, and topic drift. They emphasize the need for domain adaptation models and noise-resilient architecture.

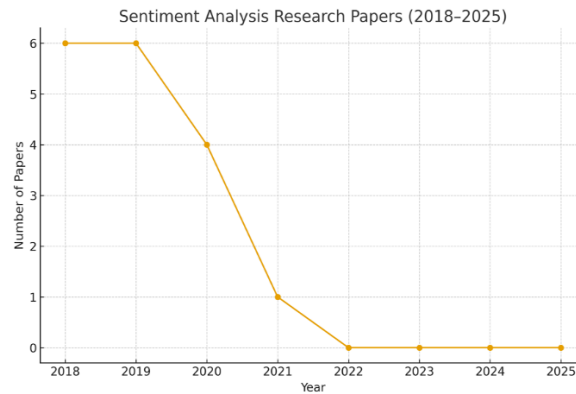


Fig 1: Sentiment Analysis Research Papers 2018 to 2025

Figure 1 illustrates the publication trend of sentiment analysis research papers from 2018 to 2025 based on the studies reviewed in this work. The graph shows how research activity has varied over time, highlighting specific years where significant contributions were made. From the graph, it is evident that 2018 and 2019 were the most productive years, each contributing six major research papers to the field. This surge reflects the rapid adoption of deep learning methods—such as LSTM, CNN, BiLSTM, and GRU, which became widely used during these years. The consistent high output in these two years indicates strong research interest and development in NLP and sentiment analysis. In 2020, the number of publications slightly declined to four. Despite the reduction, this period marks growing interest in hybrid architectures and contextual models, including the introduction of models integrating CNN–LSTM combinations and early transformer-based techniques. The trend continues downward in 2021, with only one major study identified. This decline may be attributed to researchers shifting toward broader transformer-based NLP tasks rather than traditional sentiment classification.

2.2 MACHINE LEARNING APPROACHES

2.2.1 Pujari & Shetty (2018) – Comparative Classifier Analysis

This study compares traditional classifiers (SVM, Naïve Bayes, Decision Trees, Random Forests) for feature-oriented sentiment tasks. Their findings show that SVM consistently outperforms other methods for high-dimensional text due to its ability to handle sparse data efficiently. However, the model requires extensive pre-processing and manual feature selection, demonstrating the limitations that DL later overcomes.

2.2.2 Fang & Zhan (2015) – Early ML in Product Reviews

The paper uses bag-of-words and TF-IDF representations. It is representative of pre-deep learning research, which relied heavily on statistical learning. Although simple, this approach forms the baseline for evaluating successive improvements.

2.3 DEEP LEARNING-BASED SENTIMENT MODELS

2.3.1 Sreesurya et al. (2020) – Enhanced LSTM for Business Intelligence

Hypex, the tool developed in this work, combines LSTM layers with optimized training modules to extract business intelligence signals from reviews. The model handles long text effectively and captures semantic flow better than ML models. Results show improved accuracy and stability across multiple datasets.

2.3.2 Rani & Kumar (2019) – CNN for Hindi Sentiment Analysis

This work demonstrates the applicability of convolutional neural networks for sentiment extraction in Indian languages, focusing on Hindi movie reviews. The challenge addressed here is the scarcity of labeled datasets and the morphological richness of Indian languages. CNNs perform well due to their ability to detect local patterns and n-gram features through convolution filters.

2.3.3 Ahmed & Ghabayen (2020) – BiGRU Framework

This framework adopts a two-phase model: sentiment polarity detection followed by rating prediction. The BiGRU architecture captures long-range dependencies with a lighter computational footprint compared to LSTM, making it suitable for large review datasets such as Yelp and Amazon.

2.3.4 Singh et al. (2017) – Optimized Deep Learning Classifiers

This research focuses on hyperparameter tuning and model selection. It concludes that hybrid architecture often outperforms standard CNN/LSTM models because they combine local feature extraction with global context modeling.

2.3.5 Souza et al. (2018) – Deep Learning for Hotel Reviews, Hotel reviews typically contain multiple aspects: service, cleanliness, food, value, and amenities. This work addresses multi-aspect sentiment and shows that DL models outperform traditional models significantly in hospitality dataset

2.3.6 Ghorbani et al. (Hybrid CNN–BiLSTM Model).

This paper proposes hybrid architecture that uses CNNs for spatial features and BiLSTMs for sequential dependencies. The model achieves higher accuracy compared to standalone CNN or LSTM variants, showing clear benefits of architectural hybridization.

2.4 ASPECT-BASED AND FEATURE-DRIVEN SENTIMENT STUDIES

2.4.1 Albornoz et al. (2011) – Joint Feature Mining and Sentiment Rating

One of the earliest works in ABSA, this study introduced methods to simultaneously extract features and predict sentiments. It highlights the importance of feature dependency and the relationship between review components

2.4.2 Suryadi & Kim (2017) – Sentiment-Dependent Product Features

This paper proposes methods to identify features that influence sentiment the most. It moves beyond simple polarity analysis and explores how contextual dependencies can identify the most impactful product characteristics.

2.4.3 Chen et al. (2019) – OPSM + PrefixSpan Pattern-Based Sentiment Analysis

This innovative work employs pattern mining techniques to discover frequent sentiment-bearing patterns in reviews. By integrating OPSM biclustering with sequential pattern mining, their model achieves very high accuracy (over 90%) across benchmarks.

2.5 CONTEXTUAL AND TEMPORAL MODELS

2.5.1 AL-Sharuee et al. (2021) – Temporal Sentiment Clustering

This work introduces the ACAEC system for clustering reviews based on temporal and contextual patterns. It is particularly useful for detecting evolving trends, seasonal sentiments, or changing product performance over time.

2.5.2 Huddar et al. (2021) – Context-Driven BiLSTM

A context-aware model that integrates forward and backward LSTM states to better capture semantic polarity in long texts. The paper reports consistent 2–3% accuracy improvements across multiple benchmark datasets.

2.5.3 Krishna et al. (2021) – Cross-Domain ELMo-Based Sentiment Analysis

The authors explore domain transfer using ELMo embeddings. Their model performs well on Twitter, achieving 78.8% accuracy despite the domain shift, demonstrating the benefit of contextual embedding.

2.6 DECEPTIVE REVIEW DETECTION

2.6.1 Jain et al. (2019) – Hierarchical Multi-Instance Learning

This work focuses on detecting fake reviews. The authors propose CNN–GRU hybrid networks to model review authenticity. They show that deceptive reviews have distinct writing patterns, and deep models detect these more effectively than classical methods.

Paper / Author	Focus Area	Methodology Used	Key Contribution / Findings
Himmat & Salim (2014)	Survey on product-review sentiment classification	Classical ML, lexicon analysis	Identified challenges: feature sparsity, domain-dependence, negation handling, intensifiers.
Vishwakarma (2020)	Deep learning survey	CNN, LSTM, BiLSTM, GRU, Attention, Word Embeddings	Showed shift from manual feature engineering → automatic representation learning using embeddings.
Hemmatian & Sohrabi (2019)	Survey on classification methods	Supervised, unsupervised, lexicon+ML hybrid	Highlighted failure of lexicons with slang; importance of data-driven approaches.
Yue et al. (2019)	Social media sentiment analysis survey	Social-media-specific preprocessing	Addressed challenges: emojis, hashtags, abbreviations, noise, domain drift.
Pujari & Shetty (2018)	Classifier comparison	SVM, Naïve Bayes, Decision Trees, Random Forest	SVM performed best for high-dimensional sparse text; heavy feature engineering required.
Fang & Zhan (2015)	Early product-review ML	TF-IDF, Bag-of-Words	Provided foundational ML baselines before DL emergence.
Sreesurya et al. (2020)	Business-intelligence sentiment	Enhanced LSTM architecture (Hypex tool)	High stability & accuracy on long-text review datasets.
Rani & Kumar (2019)	Hindi sentiment classification	CNN model	Effective on morphologically rich languages; strong n-gram feature detection.
Ahmed & Ghabayen (2020)	Review polarity + rating prediction	BiGRU, Two-phase hybrid	Computationally efficient; strong performance on Yelp/Amazon.
Singh et al. (2017)	Improved DL classifier	CNN–LSTM hybrid	Demonstrated hyperparameter impact; hybrids > individual models.
Souza et al. (2018)	Hotel review sentiment	DL multi-aspect modeling	Outperformed ML in multi-feature hospitality datasets.
Ghorbani et al.	Hybrid sentiment model	CNN + BiLSTM	Captures spatial + sequential dependencies; higher accuracy.
Albornoz et al. (2011)	Joint feature mining + sentiment rating	Feature mining + sentiment mapping	Early ABSA approach; extracted feature-sentiment dependencies.
Suryadi & Kim (2017)	Feature-sentiment dependency	Context-driven feature extraction	Identified which product features most influence sentiment.

Chen et al. (2019)	Pattern-based sentiment	OPSM + PrefixSpan pattern mining	Achieved >90% accuracy; strong feature interpretability.
AL-Sharuee et al. (2021)	Temporal sentiment clustering	ACAEC clustering algorithm	Tracks time-based sentiment shifts; useful for trend forecasting.

Table 1: literature survey and methodology used

Table 2: latest literature survey report

Year	Paper / Title / Summary	Relevance / Notes
2025	Optimized hybrid deep learning for cross-linguistic sentiment analysis: a novel approach — Journal of Cloud Computing, 2025. SpringerLink	Proposes a hybrid CNN + LSTM model optimized for multilingual sentiment analysis. Good for expanding into multilingual / cross-lingual review sentiment tasks, beyond monolingual English — akin to cross-domain contextual embedding ideas.
2025	An analytical assessment of sentiment analysis trends and methods through systematic review and topic modeling — Decision Analytics Journal, 2025. ScienceDirect	This is a large-scale systematic review covering ~14,482 sentiment-analysis articles (2012–2024), showing the shift from lexicon/ML to deep-learning (CNN, LSTM, Transformers). It is useful to situate this work historically/trend-wise and see research gaps.
2024	Transforming sentiment analysis for e-commerce product reviews: Hybrid deep learning model with an innovative term weighting and feature selection — Information Processing & Management, 2024. ScienceDirect	Focused on product reviews (e-commerce) using a hybrid DL model (with term-weighting + feature selection + LSTM). Directly relevant to this product-review sentiment analysis line.
2024	Sentiment Analysis of Product Reviews Using Transformer-Enhanced 1D-CNN and BiLSTM — Cybernetics and Information Technologies, 2024. Paradigm	Combines Transformers + CNN + Bi-LSTM for product-review sentiment — a “stacked / hybrid” modern design, similar in spirit to older Bi-LSTM or ELMo/embedding-based approaches, but with newer architectures.
2025	Research on web text sentiment analysis and application based on Deep Learning — Advances in Engineering Innovation, 2025. Ewa Direct	A recent survey / review discussing deep-learning based sentiment analysis for web/social media text, highlighting modern challenges: long texts, pre-trained models, cross-language, real-world applications. Good for framing background + future work.
2024	Challenges and future in deep learning for sentiment analysis: a comprehensive review and a proposed novel hybrid approach — Artificial Intelligence Review, 2024. SpringerLink	A comprehensive recent review of deep-learning sentiment analysis, discussing taxonomy, methods (RNN, CNN, transformers), gaps (domain adaptation, interpretability), and proposing a hybrid model. Useful for literature surveys and identifying open problems.

3. METHODOLOGY USED IN LITERATURE

This section summarizes common methodologies extracted from the reviewed papers. The methodologies used across these research papers can be grouped into preprocessing methods, feature extraction strategies, machine learning techniques, deep learning architectures, hybrid approaches, and contextual embedding models. Preprocessing steps include tokenization, stop-word removal, stemming, lemmatization, normalization of slang, emoji handling, and negation recognition. Feature extraction evolved from bag-of-words (BoW) to TF-IDF and then to dynamic embedding techniques. Machine learning approaches such as Naïve Bayes and SVM rely heavily on statistical features and require careful tuning of hyperparameters. Deep learning approaches, on the other hand, learn feature representations automatically. CNNs extract spatial features, LSTMs capture sequential patterns, and BiLSTMs combine forward and backward context. GRUs offer a lighter alternative to LSTMs. Hybrid models blend the strengths of CNNs and LSTMs.

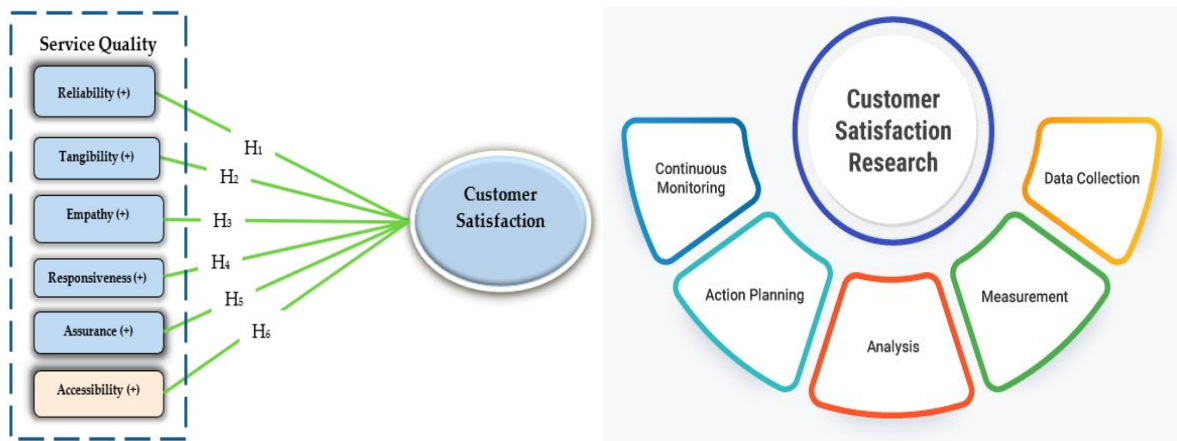


Figure 2: (a)Customer Satisfaction (b) Research Steps for Customer Satisfaction

First, Figure 2 (a) and (b) reflect the level of customer satisfaction. Transformer-based models such as BERT and ELMo add contextual understanding by generating embedding based on entire sentence semantics rather than isolated word vectors. These models represent the latest evolution in sentiment analysis and consistently achieve state-of-the-art results. Pattern mining and aspect extraction techniques enhance explainability, enabling organizations to precisely understand which aspects influence user sentiment. Temporal models track how public opinion evolves over time, allowing predictive insights in marketing, politics, and crisis management.

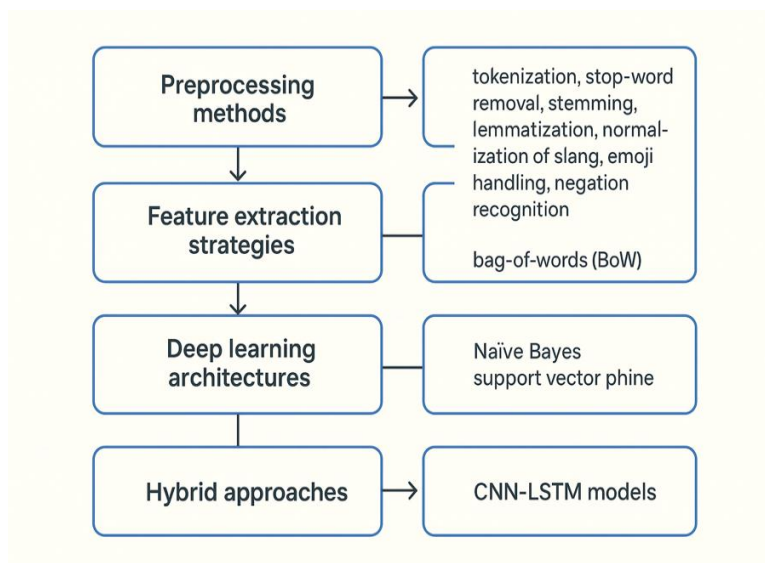


Figure 3: Flow of common methodologies extracted from the reviewed papers

Figure 3 presents the sequential workflow used in sentiment analysis research, beginning with data pre-processing techniques like tokenization, stop-word removal, and text normalization. It then moves toward feature extraction methods such as TF-IDF and word embeddings. Machine learning and deep learning models are applied next to classify sentiment effectively. The flow highlights how each step builds upon the previous one to ensure accurate and meaningful sentiment prediction.

3.1 Data Pre-processing

Common steps includes in data pre-processing are as given below:

- Tokenization
- Stop-word removal
- Lemmatization or stemming
- Handling emojis/emoticons (especially for social media)
- Negation handling
- Normalization of slang or informal words
- Vectorization (TF-IDF, Bag-of-Words, Word2Vec, GloVe)



Figure 4: Data Pre-processing Steps

Figure 4 illustrates the essential data pre-processing steps required to clean and prepare textual data before applying sentiment analysis models. The process begins with tokenization, which breaks text into individual words or meaningful units. Stop-word removal eliminates commonly used but non-informative words such as “the,” “is,” and “and.” Lemmatization or stemming reduces words to their base form, ensuring that similar words (e.g., “running,” “runs”) are treated uniformly. The figure also highlights the importance of handling emojis and emoticons, which often convey strong emotions in social media text. Negation handling ensures that expressions like “not good” are interpreted correctly. Finally, vectorization transforms the cleaned text into numerical formats (e.g., TF-IDF, Word2Vec, GloVe) that machine learning and deep learning models can process effectively.

3.2 Machine Learning Techniques

- **SVM:** Works well for high-dimensional sparse text.
- **Naïve Bayes:** Performs well on short text but assumes feature independence.
- **Random Forests / Decision Trees:** Useful for interpretable classification.
- **Logistic Regression:** Baseline ML model for sentiment tasks.

Limitations: heavy dependency on hand-engineered features.

3.3 Deep Learning Techniques

CNN: Captures local word patterns; useful for short reviews or sentences.

LSTM / BiLSTM: Handles long sequences; captures forward/backward context.

GRU / BiGRU: Computationally efficient alternative to LSTM.

Hybrid Models: Combine CNN + LSTM or CNN + GRU for improved performance.

Attention Mechanisms: Highlight important words in a sentence.

Transfer Learning: ELMo, BERT, GPT-style transformers are modern advancements (not included in earlier papers but relevant).

3.4 Pattern Mining and Feature-Based Approaches

- Sequential pattern mining
- Biclustering
- Opinion phrase extraction
- Feature dependency graphs

These models improve interpretability and fine-grained sentiment analysis.

3.5 Temporal and Contextual Models

- Trend detection
- Seasonal analysis
- Dynamic sentiment modeling
- Cross-domain adaptability

4. CONCLUSION

A comprehensive review of 20+ research papers shows that sentiment analysis has evolved remarkably over the past decade. The evolution of sentiment analysis has been remarkable. From simple lexicon-based models to advanced transformer architectures, sentiment classification techniques have continuously improved in accuracy and applicability. Deep learning models revolutionized the domain by removing the dependency on manual feature engineering and enabling context-aware sentiment prediction. However, several limitations remain. Models still struggle with sarcasm, irony, cultural context, and multilingual sentiment representation. Domain adaptation remains an open issue, as models trained on one dataset often perform poorly when applied to another. Additionally, deep learning models, while accurate, often lack explainability, making it difficult for organizations to trust their predictions without interpretability mechanisms. Future research is expected to focus on explainable AI (XAI), multimodal sentiment analysis, cross-lingual sentiment classification, transformer-based architectures (such as BERT, RoBERTa, GPT models), and robust evaluation across domains. Sentiment analysis has a bright future, and the foundation established by the reviewed research provides a strong platform for upcoming innovations. The field has progressed from lexicon-based models to complex deep learning and hybrid neural architectures capable of understanding context, semantics, temporal variance, and textual deception. Deep learning models—especially BiLSTMs, GRUs, and hybrid CNN–RNN models—consistently outperform traditional machine learning techniques across benchmarks. Future research is likely to move towards transformer-based architectures, multimodal sentiment analysis (text + images), and explainable AI. The reviewed literature provides strong foundational knowledge for constructing robust sentiment analysis frameworks.

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