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# The Evolution of Sentiment Analysis in NLP:A Review of Techniques and Applications

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***Abstract :*** Sentiment analysis (SA) has been a crucial area of study within natural language processing (NLP), progressing from early rule-based systems to more recent methods that use transformer models, deep learning (DL), and multimodal techniques. This work offers a systematic evaluation of research contributions from 2005 to 2025, emphasising important techniques such sentiment-specific embeddings, hybrid models, lexicon-based approaches, classical machine learning, and new multimodal architectures. Particular attention is paid to the integration of symbolic thinking and audio-visual elements. The paper provides practical applications, performance benchmarks, and outstanding issues such as sarcasm detection and domain adaptability by combining these various approaches. Transformer-based models and multimodal integration have been the main topics of recent contributions [1, 2, 4], whereas earlier studies established the framework using symbolic techniques that are lexicon-based and symbolic [13, 16].

***Index Terms*** : Deep Learning, Transformer Models, Lexicon-Based Models, Natural Language Processing, Sentiment Analysis, Multimodal Sentiment Analysis, Hybrid Techniques, and Emotion Recognition

## I. INTRODUCTION

The goal of sentiment analysis, also referred to as opinion mining, is to locate and extract subjective data from textual and multimedia content, including sentiments, views, and emotions. SA is now essential for corporate intelligence, healthcare monitoring, political forecasting, and more due to the rapid growth of user-generated data on websites such as Twitter, YouTube, and e-commerce platforms. Conventional SA techniques used rule-based decision trees and manually constructed lexicons. These, however, were not contextually sensitive or scalable [13, 15].

The use of ML and DL techniques has increased recently; in particular, LSTM, Bi-LSTM, and attention-based transformer architectures like BERT and RoBERTa have enhanced polarity categorisation and contextual comprehension [1, 2]. In order to enhance sentiment interpretation, researchers have dabbled in multimodal SA, which combines visual and audio cues, in parallel to textual analysis [4, 5, 6]. This work summarises important contributions from various fields, highlighting the methodological development, potential applications, and future directions.

## II. LITERATURE REVIEW

The field of sentiment analysis has undergone substantial development. The following reviews key contributions in this area:

Rahman et al. [1] compare many deep learning models, including CNN, RNN, and transformer-based architectures. The project investigates how well BERT, RoBERTa, and ALBERT perform on extensive datasets, such as reviews from Amazon and IMDb. According to their research, transformer-based models routinely perform better in terms of accuracy and contextual awareness than conventional RNN-based models. The authors stress how attention techniques are becoming more and more crucial for identifying subtleties in sentiment. Additionally, they emphasise how pretraining and fine-tuning can improve model performance for sentiment tasks that are specific to a given domain.

Mansoor et al. [2]. According to the paper, Bi-LSTM's ability to capture context in both directions led to the best result. To assess model performance, the study used a number of criteria, including accuracy, F1-score, and precision. The importance of input representations and word embeddings in assessing classification accuracy was also covered. The study ends by suggesting hybrid models that combine LSTM for context preservation and CNN for feature extraction.

Demir et al. [3] presented a hybrid sentiment classification model that combines machine learning algorithms such as SVM and Naïve Bayes with rule-based reasoning. To improve categorisation on noisy datasets, their technique incorporates syntactic patterns and lexicon dictionaries. The authors demonstrate enhanced precision and recall by evaluating their method on social media content and reviewing datasets. The study emphasises how rule-based filtering may capture colloquial terms and eliminate false positives. It also provides information about how to balance learning-based and rule-based systems in hybrid architectures.

Soleymani et al. [4]. They examined statistical and deep learning methods for fusing and synchronising multimodal data streams. The authors discussed issues with dataset availability, modality dominance, and temporal alignment. Important datasets like AVEC and CMU-MOSEI were included in their investigation. Future studies on cross-modal emotion identification algorithms for application in interactive media and video blogs were made possible by this paper.

Majumder et al. [5] used hierarchical attention networks to create a system for detecting personality and sentiment at the document level. Their framework captures deep semantic meaning by modelling text at the word and sentence levels. The model is used to identify personalities in customer reviews and social media posts. The findings indicate a substantial relationship between reported sentiments and particular personality features. The authors suggest new standards for personality-sentiment alignment and highlight the psychological and linguistic interactions in lengthy opinion texts.

Tang et al. [6]. Compared to general-purpose embeddings like Word2Vec or GloVe, these embeddings are more effective for sentiment classification tasks because they are trained utilising sentiment supervision. Significant gains were made when the authors tried SSWE on datasets like MR and SST. Sentiment-aware embedding methods that improve feature representations in deep networks were made possible by their contribution.

Cambria et al. [7], sentiment analysis is a complex issue that involves a "big suitcase" full of difficulties, including affective computing, emotion mining, and sarcasm recognition. They underlined the necessity of hybrid systems that integrate machine learning with symbolic AI. In order to facilitate deep sentiment inference, the paper presents SenticNet, a commonsense knowledge base, and talks about the drawbacks of strictly statistical models. In order to tackle high-level sentiment abstraction, the authors support cognitive computing techniques.

Giachanou and Crestani [8] conducted a thorough investigation of sentiment analysis on Twitter. They divided sentiment analysis techniques into three categories: hybrid, lexicon-based, and machine learning. The study covered topics such as time sensitivity in tweets, hashtag management, and abbreviation processing. Additionally, they contrasted classification algorithms such as SVM and Naïve Bayes with feature extraction techniques. For researchers working on short-text sentiment analysis on microblogging sites, their work continues to be a vital resource.

Sentic Computing, a model for emotion-sensitive computing based on semantic networks and commonsense reasoning, was first presented by Cambria et al. [9] in this early foundational study. Beyond sentiment terms at the surface level, the article suggests a tiered architecture for sentiment systems. Additionally, it combines semantic role labelling and affective reasoning to enhance sentiment detection in practical applications. Feature enrichment and polarity assignment are done with SenticNet, a sentiment-enhanced knowledge graph.

Whitelaw et al. [10] introduced an appraisal-based sentiment classifier that can identify sentiment. By taking into account grammatical roles and language structures, their method goes beyond conventional bag-of-words models. News articles and product reviews were used to train and test the classifier. Early foundations for integrating linguistic theory into statistical sentiment models were established by the study. It is still important for creating context-aware natural language processing systems.

Soleymani et al. [11] presented and examined a number of multimodal sentiment datasets, such as DEAP, MAHNOB, and CMU-MOSEI, in a follow-up study to their previous survey. The study outlines evaluation processes, labelling practices, and modal-specific difficulties. These tools are now considered industry standards for multimodal sentiment model training and validation. The work emphasises how crucial cross-modal consistency and unifying annotation approaches are when creating datasets.

Using the Stanford Sentiment Treebank, Socher et al. [12] created Recursive Neural Tensor Networks (RNTNs) for sentiment analysis. Their model parses sentence structures into binary trees in order to learn compositional sentiment. This method generates more detailed sentiment predictions by capturing sentiment changes across phrases and clauses. The study remained a fundamental deep learning technique for structured sentiment problems and made substantial progress in understanding the relationship between syntax and sentiment.

Poria et al. [13] to propose a multimodal sentiment classifier. To identify emotions, the model combines elements from visual, aural, and textual clues. High accuracy was shown in experiments on benchmark datasets such as IEMOCAP for a variety of sentiment categories. The study encouraged more investigation into fusion strategies for multimodal learning and emphasised the benefits of kernel-based fusion techniques over straightforward concatenation.

The problem of visual sentiment analysis in animated GIFs was addressed by Jou et al. [14]. They presented a deep learning model that aligns video frames with sentiment tags by learning spatiotemporal features. Their method modelled the dynamics of motion and appearance using CNNs and RNNs. In support of social media content analysis, the study provides new avenues for sentiment recognition in transient and highly visual formats such as memes and brief videos.

SentiBank, a visual idea detector based on sentiment-related adjectives and nouns, was presented by Borth et al. [15]. Their model bridges the semantic gap between affective states and visual data by using thousands of Adjective Noun Pairs (ANPs). It is still one of the first extensive visual emotion databases and was tested on YouTube and Flickr content. Numerous contemporary visual affect recognition systems have been impacted by the work.

Prior to using machine learning models, Pang et al. [16] proposed a method for sentiment categorisation that includes subjectivity summarisation. They demonstrated that classification accuracy is increased when objective sentences are eliminated from evaluations. They trained Naïve Bayes and SVM models on subjective parts of the texts using movie reviews. This approach is still used in sentiment-based summarisation tasks and was a part of the first sentiment modelling pipelines.

| **Author(s)** | **Year** | **Focus Area** | **Techniques/Models** | **Application Domains** | **Unique Contributions** |
|---|---|---|---|---|---|
| Rahman et al. [1] | 2024 | Transformer Models | BERT, RoBERTa | Amazon Reviews | RoBERTa outperformed all others |
| Mansoor et al. [2] | 2023 | Deep Learning Comparisons | CNN, RNN, Bi-LSTM | IMDb, Twitter | Bi-LSTM showed best accuracy |
| Demir et al. [3] | 2023 | Hybrid SA Model | ML + Rule-Based Fusion | Product Reviews | Flexible, high-accuracy framework |
| Soleymani et al. [4] | 2017 | Multimodal SA Survey | Audio-Visual Fusion | YouTube, Social Media | Benchmarked multimodal sentiment systems |
| Majumder et al. [5] | 2017 | Personality & Sentiment Fusion | CNN + Feature Injection | Recommender Systems | Big Five trait extraction from text essays |
| Tang et al. [6] | 2016 | Word Embeddings | Sentiment-Specific Vectors | Tweets, Reviews | Separation of sentiment polarities in embeddings |
| Cambria et al. [7] | 2017 | Symbolic + Subsymbolic NLP | 3-layer NLP Architecture | General NLP Tasks | Multi-layered SA problem breakdown |
| Giachanou & Crestani [8] | 2016 | Twitter Sentiment Survey | Lexical + ML Methods | Microblogs | First taxonomy of Twitter sentiment techniques |
| Cambria et al. [9] | 2012 | Affective Computing | SenticNet, Knowledge Graphs | General SA | Semantic affective sentiment framework |
| Whitelaw et al. [10] | 2005 | Appraisal Theory in SA | Semantic Taxonomies | Movie Reviews | High-accuracy rule-based system |
| Soleymani et al. [11] | 2017 | Multimodal Dataset Benchmark | Text + Audio + Facial cues | Social Videos | Rich multimodal datasets |
| Socher et al. [12] | 2013 | Recursive Deep Models | RNTN | Phrase-level Sentiment | Semantic compositionality in tree structures |
| Poria et al. [13] | 2016 | Multimodal Sentiment Fusion | CNNs, Visual + Textual | Video Content | Unified multimodal sentiment model |
| Jou et al. [14] | 2015 | Visual Sentiment Concept | SentiBank | Images, GIFs | Sentiment prediction from visual content |
| Borth et al. [15] | 2013 | Ontology-Based Emotion Analysis | Visual Ontologies | Multimedia | Visual sentiment emotion classifiers |
| Pang & Lee [16] | 2004 | Subjectivity Summarization | SVM, Cuts | Text Classification | Early sentiment classification using ML |

**Table 1.1: Researchers' Work**

## III. CONCLUSION

In conclusion from organised, lexicon-driven frameworks to robust, data-driven, multimodal systems, sentiment analysis has advanced. Every generational transition, from ML to DL to Transformer models, has addressed previous issues while revealing new ones, including as multimodal fusion, explainability, and cross-domain transfer. Sentiment modelling may become more human-like by incorporating linguistic theories, symbolic AI, and affective computing concepts. To create more inclusive and reliable sentiment analysis applications, future research should give interpretability, cross-cultural sentiment adaption, and ethical AI top priority.

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