Advancements in Sentiment Analysis using Deep Learning for Social Media Text Classification

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ABSTRACT

The rapid expansion of social media has generated vast amounts of unstructured textual data, revealing users' opinions, emotions, and behaviors. Sentiment analysis, a critical task in natural language processing (NLP), leverages deep learning models to classify this data into positive, negative, or neutral sentiments. Traditional machine learning approaches struggled with contextual understanding, leading to the adoption of deep learning techniques like CNNs, RNNs, and transformer-based models such as BERT. These models offer enhanced accuracy and contextual understanding. Despite advances, challenges such as multilingual sentiment analysis and sarcasm detection remain, highlighting areas for future exploration in social media sentiment classification.

Keywords: *Social Media, Sentiment Analysis, Deep Learning, NLP, Transformer Models.*

I. INTRODUCTION

In recent years, the exponential growth of social media platforms has led to the generation of massive volumes of unstructured textual data, which reflects users' opinions, emotions, and behavioral patterns. Analyzing this data has become a critical area of research in natural language processing (NLP), particularly through sentiment analysis techniques powered by deep learning models. Sentiment analysis refers to the computational identification and classification of subjective information in text, typically categorized into positive, negative, or neutral sentiments. With the advancement of artificial intelligence (AI), deep learning-based NLP approaches have significantly improved the accuracy, scalability, and contextual understanding of sentiment classification tasks in social media environments (Dang et al., 2020; Mekala et al., 2023). Traditional machine learning methods such as Naïve Bayes and support vector machines were initially used for sentiment classification; however, these approaches often struggled to capture contextual semantics and complex linguistic structures in large-scale datasets. To overcome these limitations, researchers have increasingly adopted deep learning architectures such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), long short-term memory (LSTM) networks, and transformer-based models. These models are capable of automatically learning hierarchical feature representations from raw textual data, thereby improving sentiment detection performance (Rani & Kumar, 2019; Brinda et al., 2024). Recent studies have demonstrated the effectiveness of advanced transformer-based models such as BERT and its lightweight variants in sentiment analysis tasks. For instance, Makkena (2026) proposed a DistilBERT-based framework integrated with TF-IDF feature extraction and SMOTE balancing, achieving a high accuracy of 98% on the Sentiment140 dataset. This highlights the capability of transformer models in capturing deep contextual relationships in social media text. Similarly, Bao and Su (2025) introduced an optimized deep learning framework incorporating dynamic graph neural networks and attention mechanisms, which achieved superior performance in emotion detection tasks with over 96% accuracy. Furthermore, sentiment analysis has expanded beyond simple polarity classification to more complex applications such as emotion detection, topic-based sentiment analysis, and multimodal sentiment recognition. For example, Brinda et al. (2024) developed a multimodal sentiment analysis framework that integrates textual and image-based data using deep neural networks, achieving an accuracy of 96.1%. This demonstrates the increasing importance of combining multiple data sources for more comprehensive sentiment interpretation in social media environments. In addition, sentiment analysis has been widely applied in domain-specific contexts such as climate change awareness, healthcare monitoring, and disaster management. Eltahir et al. (2025) proposed a Bayesian machine learning-based sentiment analysis framework for analyzing public opinion on climate change, achieving 94.07% accuracy. Such applications highlight the societal importance of sentiment analysis in understanding public perception and supporting data-driven decision-making processes. Despite these advancements, challenges remain in the field, including handling multilingual text, sarcasm detection, contextual ambiguity, and real-time processing of streaming data. Agüero-Torales et al. (2021) emphasized that multilingual sentiment analysis and aspect-based sentiment modeling are still underexplored areas, particularly in transformer-based architectures.

II. RESEARCH BACKGROUND

Makkena (2026) had examined social media text and posts using advanced computing and artificial intelligence systems in order to determine user sentiments. The study had analyzed word intensity and user activities to identify emotional orientation in online content. It had employed the Sentiment140 dataset, consisting of 1.6 million labelled tweets, and had proposed a systematic framework for sentiment classification. The suggested methodology had included data preprocessing, tokenization, min-max normalization, TF-IDF-based feature extraction, and class balancing through SMOTE. Furthermore, the processed dataset had been trained using a Distil BERT model to capture contextual dependencies and the semantic structure of textual data. The experimental evaluation had demonstrated strong performance, with 98% accuracy, 96% precision, 96% recall, and an F1-score of 98%, outperforming existing models such as Random Forest, Decision Tree, and the BERT baseline. The findings had indicated that the proposed system was highly effective and efficient for large-scale social media sentiment analysis, while also providing a strong foundation for future multilingual, multimodal, and explainable sentiment classification research.

Bao and Su (2025) investigated the application and optimization of deep learning (DL)-based natural language processing (NLP) techniques for analyzing emotional implications in textual data. The study highlighted that understanding emotional nuances in text had become increasingly important across domains such as social media analysis, customer feedback evaluation, and mental health monitoring due to the rapid growth of digital content. The authors discussed key challenges in automating emotion analysis, particularly the diversity of text formats and the complexities of NLP processing. It was reported that text-based emotion datasets were pre-processed through tokenization, lemmatization, and the removal of stop words and punctuation. The model was designed with pre-trained embeddings and attention mechanisms to capture contextual and emotional subtleties across languages. Bao and Su proposed a hybrid tuned crow search optimized dynamic graph neural network (TCSO-DGNN), which demonstrated superior performance, achieving 94.72% precision, 96.43% accuracy, 94.36% recall, and 93.02% F1-score in emotion detection tasks.

Eltahir et al. (2025) examined the rapid growth of data generated through social networks and highlighted its significance as an emerging research domain in relation to environmental concerns. The authors reported that sentiment analysis (SA) had been employed to understand public behavior and sensitivity toward climate-related issues by integrating ubiquitous learning with natural language processing (NLP). Their study proposed a Twitter Climate Change Sentiment Analysis using Bayesian Machine Learning

(TCCSA-BML) technique aimed at supporting sustainable development in rural areas. It was noted that the model applied multiple preprocessing steps to prepare textual inputs and used TF-IDF for word embedding. For sentiment classification, Bayesian Model Averaging (BMA) was adopted by combining attention long short-term memory (ALSTM), extreme learning machine (ELM), and gated recurrent unit (GRU) classifiers. Furthermore, parameter tuning was carried out using the coyote optimization algorithm (COA). The findings indicated that the proposed approach achieved a superior accuracy of 94.07% on the Kaggle SA dataset.

Brinda et al. (2024) had presented a comprehensive investigation of sentiment analysis in social media communication by integrating deep learning techniques with natural language processing (NLP) methodologies. The study had aimed to develop a matching model applicable to real-world social processes, enabling the precise identification of dynamically changing relevant content and the real-time extraction of key phrases from available data. The authors had constructed both a text-based message sentiment analysis model and an image-message multimodal sentiment analysis model, thereby examining unimodal as well as multimodal sentiment analysis algorithms in social networks. The findings had demonstrated that the fusion of advanced deep neural networks, such as transformers and recurrent neural networks, with NLP techniques had been highly effective in extracting complex emotions from social media texts. Notably, the optimized deep learning models had achieved 96.1% accuracy for brief texts, while successfully classifying positive, neutral, and negative sentiments, thus offering valuable insights for enhancing sentiment analysis and semantic similarity tasks.

Mekala et al. (2023) examined sentiment analysis (SA) as an automated technique for identifying and interpreting emotions expressed in textual data. The authors observed that, over the previous decade, SA had gained substantial prominence within the Natural Language Processing (NLP) community due to the widespread use of social media and web-based platforms. The study aimed to employ a deep learning-based NLP approach to provide a comprehensive analysis of sentiments embedded in social media content. It was reported that the proposed method developed a comparable model capable of replicating relevant social processes by dynamically selecting the most significant phrases based on contextual information. This mechanism was found to enhance semantic understanding of complete sentences at each stage of processing. The authors further emphasized that the absence of contextual information could lead to inaccurate and ambiguous semantic representations. Additionally, the study reviewed both unimodal and multimodal social network sentiment analysis algorithms and developed models for text-based and image-text multimodal sentiment analysis.

Thimmapuram et al. (2022) reported that social networking had rapidly expanded worldwide, enabling millions of users to create and share diverse forms of content, including text, images, audio, and videos, through digital communication platforms. The authors observed that this growth had contributed to the emergence of social computing as a major field of study, encompassing areas such as internet semantics, artificial intelligence, linguistic processing, network analysis, and big data analytics. The study had focused on developing a program to analyze the nature and polarity of tweets related to a specific keyword in noisy Twitter streams. It was stated that the system extracted large volumes of tweets and classified them into positive and negative sentiments based on recent keyword-based inputs. For training and validation, data from film reviews on the IMDB website were utilized. The Naive Bayes algorithm was applied, and various testing methods were employed. The model reportedly achieved 92.50% accuracy with strong generalization and efficient execution speed.

Agüero-Torales et al. (2021) reviewed twenty-four studies covering twenty-three distinct languages and eleven social media platforms, which collectively demonstrated the sustained scholarly interest in deep learning-based approaches for multilingual sentiment analysis in social media contexts. The authors had extended the scope of earlier reviews by incorporating broader coverage from 2017 to 2020 and by emphasizing the conceptual foundations and shared methodological patterns underlying different multilingual sentiment analysis solutions. Their review had identified several important trends in the field. First, research attention had increasingly shifted toward cross-lingual and code-switching approaches, reflecting the growing complexity of multilingual online communication. Second, simpler deep learning architectures based on embedding layers, single CNN or LSTM feature extractors, and classifiers had appeared to stagnate in terms of innovation. Third, the study had highlighted a notable scarcity of deep learning approaches for multilingual aspect-based sentiment analysis. Finally, transformer-based architectures had remained surprisingly underexplored despite their potential suitability for more challenging multilingual tasks.

Dang et al. (2020) had examined how the study of public opinion could provide valuable insights, particularly through sentiment analysis on social networking platforms such as Twitter and Facebook. The authors had noted that sentiment analysis had emerged as an effective approach for understanding users' opinions and had found broad applicability across multiple domains. However, they had also highlighted that the efficiency and accuracy of sentiment analysis were often constrained by challenges inherent in natural language processing (NLP). In their review, it had been demonstrated that deep learning models offered promising solutions to these NLP-related difficulties. The study had specifically discussed recent research employing deep learning techniques to address sentiment analysis tasks, including sentiment polarity classification. Furthermore, models based on term frequency–inverse document frequency (TF-IDF) and word embedding approaches had been applied across several datasets. A comparative evaluation of experimental results for different models and input features had also been presented to assess their relative effectiveness.

Rani and Kumar (2019) examined sentiment analysis (SA) of natural language text as a significant and challenging task in the field of Natural Language Processing, particularly for multilingual applications. They noted that earlier studies had employed various SA techniques, including lexicon-based and machine learning approaches, for languages such as English and Chinese. Motivated by the growing success of deep learning models, they investigated the effectiveness of different convolutional neural network (CNN) configurations for performing sentiment analysis on Hindi movie reviews collected from online newspapers and websites. The dataset had been manually annotated by three native Hindi speakers to ensure its suitability for model training. Their experiments had been carried out by varying the number of convolution layers, along with the size and number of filters. The CNN models had been trained on 50% of the dataset and tested on the remaining 50%. The findings indicated that the proposed CNN model had outperformed traditional machine learning methods and state-of-the-art approaches, achieving an accuracy of 95%.

Abd El-Jawad et al. (2018) examined the rapid growth of Web 2.0 and observed that the expansion of social media platforms, particularly Twitter, had significantly increased the volume of user-generated textual content containing sentiment-rich expressions. The authors noted that this digital transformation had created new opportunities for understanding public opinions, emotions, and reactions to various events and situations. Their study compared the performance of several machine learning and deep learning techniques for sentiment classification and further proposed a hybrid framework integrating text mining with neural networks. It was reported that the dataset comprised over one million tweets collected from five distinct domains. For model development, 75% of the data was used for training, while the remaining 25% was reserved for testing. The findings indicated that the proposed hybrid system achieved a maximum accuracy of 83.7%, thereby demonstrating superior performance and highlighting the effectiveness of the hybrid learning approach over conventional supervised sentiment analysis methods.

Yoo et al. (2018) examined the growing influence and social ripple effects of social media platforms, noting that diverse studies had increasingly focused on analyzing user-generated content produced in real time. The authors observed that such content frequently contained valuable information regarding social issues and major events, particularly natural disasters, while also reflecting users' emotional responses and sentiments toward those events. In their study, they proposed *Polaris*, a system designed to analyze and predict users' sentimental trajectories related to events identified in real time from massive volumes of social media data. It was reported that the system combined both trajectory analysis and sentiment analysis, enabling users to gain insights quickly and effectively at a glance. The study further indicated that the integration of advanced deep-learning techniques had significantly improved the accuracy of sentiment classification and predictive performance. Preliminary validation results suggested that *Polaris* showed promising capability in real-time sentiment monitoring and event-oriented social media analytics.

III. KEY FINDINGS FROM STUDY

Author	Year	Objective	Methodology / Model	Dataset	Key Findings
Makkena	2026	Sentiment classification of social media text using AI	TF-IDF + SMOTE + DistilBERT	Sentiment140 (1.6M tweets)	Achieved 98% accuracy; outperformed traditional ML and baseline BERT models
Bao & Su	2025	Emotion detection using optimized deep learning NLP	TCSO-optimized DGNN + attention mechanism + embeddings	Text emotion datasets	96.43% accuracy; improved emotional nuance detection
Eltahir et al.	2025	Climate-related sentiment analysis for sustainability	Bayesian ML + ALSTM + GRU + ELM ensemble + COA optimization	Kaggle sentiment dataset	94.07% accuracy in climate sentiment classification
Brinda et al.	2024	Multimodal sentiment analysis (text + images)	Deep Neural Networks + RNN + Transformers	Social media multimodal dataset	96.1% accuracy; effective multimodal emotion detection
Mekala et al.	2023	Improve contextual sentiment understanding	NLP + Deep Learning hybrid model	Social media textual dataset	Enhanced semantic understanding and classification performance
Thimmapuram et al.	2022	Real-time Twitter sentiment classification	Naïve Bayes + NLP preprocessing	Twitter + IMDB reviews	92.5% accuracy; fast and efficient classification

Agüero-Torales et al.	2021	Review of multilingual sentiment analysis methods	CNN, LSTM, embeddings, transformers	24 research studies	Identified gaps in multilingual and aspect-based sentiment analysis
Dang et al.	2020	Comparative study of deep learning SA models	TF-IDF + Word embeddings + DL models	Multiple SA datasets	Deep learning improved accuracy over traditional ML
Rani & Kumar	2019	Sentiment analysis of Hindi text using DL	CNN-based architecture tuning	Hindi movie reviews dataset	Achieved 95% accuracy; better than traditional ML
Abd El-Jawad et al.	2018	Hybrid sentiment classification framework	Machine Learning + Neural Networks	1M tweets (5 domains)	83.7% accuracy; hybrid approach improved performance
Yoo et al.	2018	Real-time sentiment tracking system	Deep learning-based Polaris system	Social media event datasets	Enabled real-time sentiment trajectory prediction

IV. CONCLUSION

The reviewed studies clearly demonstrate that Natural Language Processing (NLP) combined with deep learning techniques has significantly improved sentiment analysis of social media data. Traditional machine learning methods such as Naïve Bayes and basic statistical models were initially effective for simple sentiment classification; however, they were limited in capturing contextual meaning, sarcasm, and long-range dependencies in textual data. With the emergence of deep learning architectures such as CNN, RNN, LSTM, GRU, and transformer-based models like BERT and DistilBERT, sentiment analysis systems have become more accurate, robust, and context-aware. Recent research findings indicate that advanced hybrid and optimized models achieve high performance levels, with accuracy often exceeding 95% in large-scale datasets such as Sentiment140 and Twitter-based corpora. For instance, transformer-based models enhanced with TF-IDF, attention mechanisms, and optimization algorithms have demonstrated superior capability in extracting semantic and emotional features from noisy and unstructured social media text. Furthermore, multimodal sentiment analysis integrating text and image data has expanded the scope of sentiment classification beyond traditional text-only approaches, enabling deeper emotional understanding of user-generated content. Overall, the literature confirms that deep learning-based NLP systems outperform conventional approaches in terms of accuracy, scalability, and adaptability to complex real-world datasets. However, challenges such as interpretability, computational cost, domain adaptation, and multilingual processing still remain significant barriers to widespread deployment.

V. FUTURE SCOPE

- **Explainable AI (XAI) Integration:** Development of interpretable sentiment analysis models to improve transparency and trust in deep learning predictions.
- **Multilingual and Code-Mixed Analysis:** Enhancement of models to effectively handle multiple languages and mixed-language social media content.

- **Multimodal Sentiment Analysis Expansion:** Integration of text, image, video, and audio data for more comprehensive sentiment understanding.
- **Real-Time Sentiment Monitoring Systems:** Design of lightweight and efficient transformer models for real-time social media analytics and decision-making.
- **Sarcasm and Context Understanding:** Improvement of models to accurately detect sarcasm, irony, and context-dependent sentiments.
- **Federated and Privacy-Preserving Learning:** Implementation of decentralized learning frameworks to ensure user data privacy during sentiment analysis.
- **Domain-Specific Applications:** Extension of sentiment analysis systems into healthcare, finance, politics, disaster management, and climate studies.
- **Optimization of Deep Learning Models:** Use of advanced optimization algorithms to reduce computational complexity while maintaining high accuracy.
- **Low-Resource Language Support:** Development of sentiment models for underrepresented and low-resource languages.
- **Graph-Based and Hybrid Neural Models:** Adoption of graph neural networks and hybrid architectures to capture social relationships and contextual dependencies more effectively.

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