# Sentiment Analysis in Social Media Using Deep Neural Models

## A Comprehensive Review of Emotional Dynamics and Emerging Trends

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***Abstract:*** This study gives a clear summary of ways to spot feelings and views on social media, explaining their move from simple keyword lists to advanced AI systems such as deep neural nets and multi-source data blends. Results come from 22 trustworthy articles selected carefully through rigorous screening in six major online databases. It shows modern machine learning tools - like combined CNN-RNN models, attention-based networks, transformers, and hybrid multimodal frameworks - boost precision when understanding meaning and sentiment tone. Most studies use Twitter information since its freely accessible and refreshed in real time. Still, challenges persist including sarcasm detection, multilingual differences, topic shifts, small labeled samples, along with ethical concerns about personal data and skewed predictions. The review highlights fresh options with knowledge-driven models and graph structures, incorporating text, audio, or visuals. Yet, the study emphasizes stable datasets, clear processing rules, along with cross-platform efficiency to boost dependable emotion recognition in social media contexts.

***Index Terms* - Opinion mining; social media; social networks; sentiment analysis; sentiment polarity classification.**

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### I. INTRODUCTION

Sentiment Analysis, sometimes called opinion mining or emotion detection, became an essential field for studying feelings shared in written words. First defined around 2000, it originally aimed to spot if a comment was good, bad, or neutral. Gradually, demand rose because digital conversations expanded fast - especially on sites like Twitter, personal blogs, and discussion boards. Today, it supports work in areas ranging from market analysis to medical research, governance, learning systems, and psychological monitoring. With growing numbers sharing views online, this method allows institutions and analysts to track mood shifts and habits as they happen. Its importance grows stronger today, since online exchanges shape choices, views, and mental health. As web-based information keeps increasing, sentiment analysis becomes essential - helping decode how people collectively feel across digital platforms.

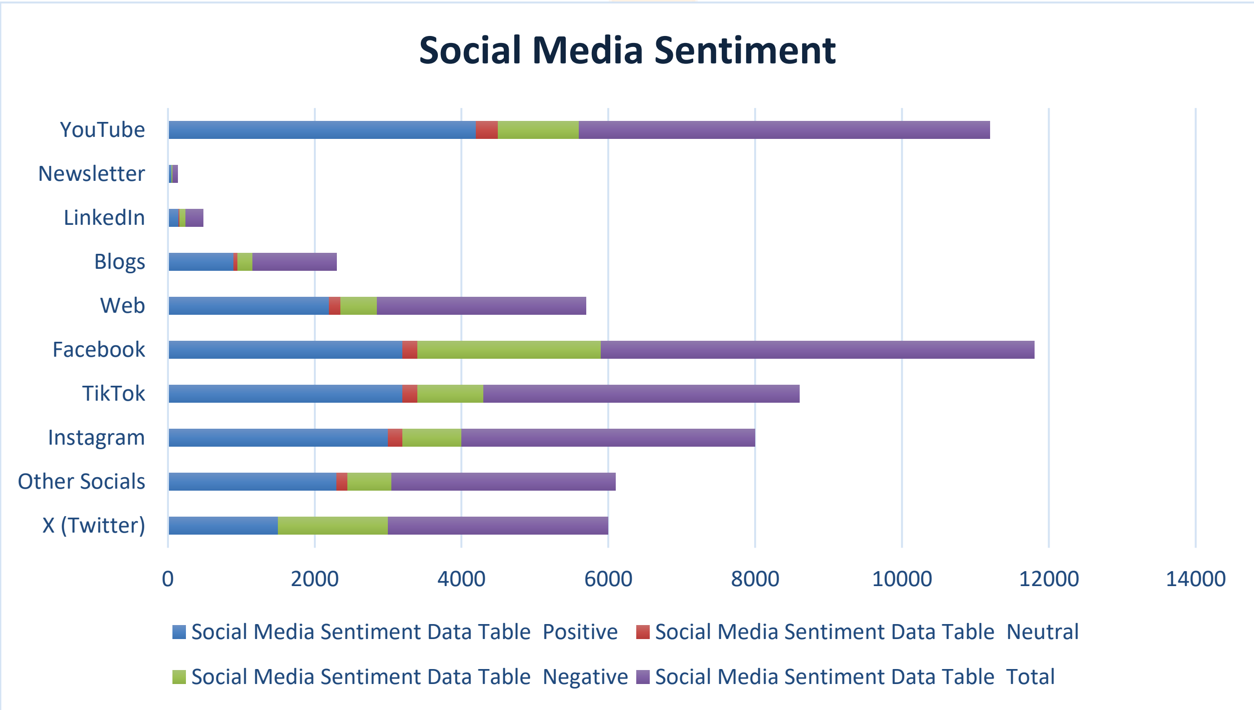


**Fig 1: Negative, Neutral and Positive sentiment over social media**

### EVOLUTION OF SENTIMENT ANALYSIS IN SOCIAL MEDIA

The rise of sentiment analysis came from progress in NLP combined with machine learning, moving away from simple rule-based methods to smarter computational systems. At first, SA relied heavily on predefined word lists paired with manually created rules; now, tools apply ML models such as Naive Bayes, Support Vector Machines, or Random Forests - sometimes even deep networks.

Methods that blend different strategies have improved accuracy, especially for complex examples. Despite advances, issues persist in detecting sarcasm or irony, informal speech, and meanings shaped by situation. These subtle language traits often lead to mistakes, reducing reliability in emotionally charged contexts. The growth of transformer systems - such as BERT or GPT - has improved understanding of context; yet issues persist, like dependence on narrow fields and unbalanced datasets. Because of this, researchers continue exploring enhanced designs to fix weaknesses, with the goal of achieving more reliable sentiment detection.
In mental-health research, sentiment analysis can identify early signs of sadness, anxiety, or emotional struggles. Social platforms such as Twitter, Instagram, or YouTube serve as digital diaries - users express feelings openly, creating useful insights into mood patterns. This work examines how posts influence depressive thoughts and emotional clarity using current analytical tools.

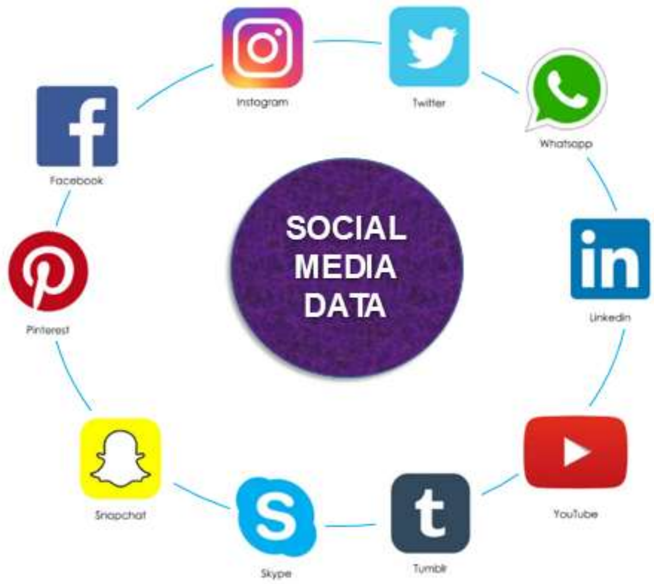


*Fig 2: Social Media Platforms*

Tools such as Naive Bayes, support vector machines, deep learning systems, along with combined approaches analyses written entries to detect shifts in mood. Still, obstacles including irony detection, unclear phrasing, plus irregular speech forms may reduce precision when classifying conditions tied to mental health. Fixing these issues matters, since errors can distort how we see someone's feelings. This study uses better systems along with context awareness - leading to clearer views of emotions while helping spot mental strain sooner. Instead of just reacting, it focuses on prediction through refined analysis methods that adjust dynamically. Each improvement builds toward more reliable results over time.

## II. METHODOLOGY OF LITERATURE REVIEW

A systematic review took place using a clear step-by-step method often seen in studies on information systems or artificial intelligence.

- Initially, our focus shifted toward shaping key questions to direct how emotions are identified across online networks.
- Second, we set specific rules for selecting studies - so only those focused on AI-based emotion detection were included.
- Third, an extensive search for key studies took place using several scholarly platforms.
- The fourth stage required choosing relevant studies by carefully reviewing titles, alongside abstracts, then keywords.
- Fifth, the chosen studies were combined by pulling out main details - like approaches, data used, frameworks, real-world use cases, while also noting results.
- Lastly, findings from the evaluation were sorted and examined - then shared within a wider conversation about new patterns, obstacles, as well as missing areas in social media sentiment and emotional analysis.

## RETRIEVING AND SELECTING

The systematic literature review was conducted using six leading scholarly databases recognized for publishing high-quality work in artificial intelligence, sentiment analysis, and multimodal analytics. These databases were IEEE Xplore, ScienceDirect, Scopus, ACM Digital Library, Emerald Insight, and PubMed. Comprehensive search strings including "sentiment analysis," "emotion detection," "multimodal sentiment analysis," "social media analytics," "deep learning sentiment models," and "AI-based text mining" were applied across all sources for the past 5 years ie., 2020 to 2025. This search initially resulted in 329 research papers: 80 from IEEE, 164 from ScienceDirect, 40 from Scopus, 21 from ACM, 25 from Emerald Insight, and 35 from PubMed/PMC. After removing non-English articles, duplicates, inaccessible full texts, and papers not directly aligned with sentiment/emotion analysis, the pool was reduced to 143 studies for preliminary screening. Titles, abstracts, and keywords were carefully reviewed to ensure relevance to NLP-based sentiment analysis, AI-driven classification, multimodal fusion, and social media opinion mining.

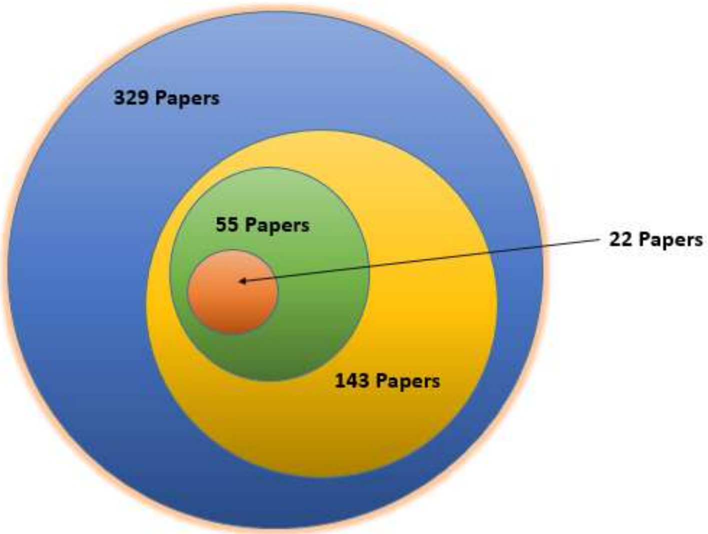


*Fig 3: Process of paper selection*

A second rigorous screening phase involved full-text examination focusing on methodological clarity, dataset quality, experimental rigor, deep learning and multimodal techniques, and relevance to modern sentiment analysis applications. Studies demonstrating outdated methods, weak evaluation metrics, or unclear datasets were excluded.

Finally, 22 high-quality papers were retained for synthesis. These included works on NLP-based sentiment extraction, multimodal fusion models, emotional AI datasets, workplace sentiment surveillance, graph neural networks, deep learning architectures, public opinion mining, lexicon–neural hybrid models, and sentiment systems for mental health assessment. The final collection provides a comprehensive foundation covering traditional machine learning, lexicon-based approaches, deep neural networks (LSTM, Bi-LSTM, CNN-BiLSTM hybrids), transformer models, multimodal fusion frameworks (KuDA, dynamic weighted models), GNNs with memory mechanisms, and social media-based emotion detection. Together, these studies form the evidence base for understanding current opportunities, technological advancements, limitations, and future directions in sentiment analysis research.

## III. LITERATURE REVIEW

Based on an in-depth analysis of the reviewed papers, the findings are presented below in a structured sequence, progressing from traditional methodologies to modern state-of-the-art approaches.

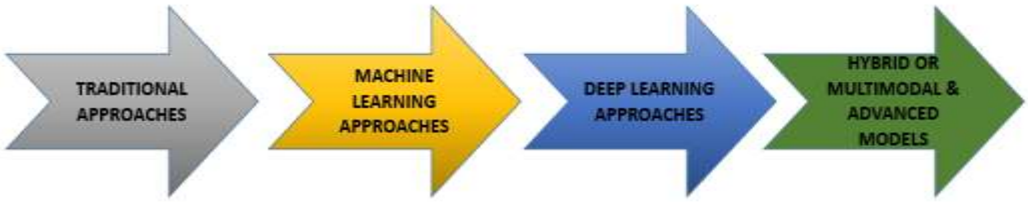


**Fig 4: Thematic structure of flow of review**

### 3.1 TRADITIONAL APPROACHES

Murat Başal presented Natural Language Processing for Sentiment Analysis in Social Media Marketing, which uses a traditional NLP-based analytical approach to extract insights from unstructured social media texts. The study uses organizational social-media marketing data, though the dataset and accuracy are not explicitly reported. However, it shows that manual analysis is less reliable than NLP-driven sentiment extraction. The limitation is that the paper does not quantify performance metrics or benchmark against modern ML/DL models.

**Emotion Analysis of Cross-Media Writing Text in the Context of Big Data**

The authors proposed Emotion Analysis of Cross-Media Writing Text using a traditional MapReduce-based combinator model for large-scale sentiment processing. It uses student Internet public-opinion texts, but the accuracy metrics are not reported. The method enhances topic-feature extraction across cross-media formats. However, its limitation lies in relying on traditional models that do not leverage modern ML/DL representations.

### 3.2 MACHINE LEARNING APPROACHES

Nirmal Varghese Babu & E. Grace Mary Kanaga presented Sentiment Analysis in Social Media Data for Depression Detection which uses machine learning and multi-class classification approaches. It uses diverse social media datasets with text, emojis, and emoticons, although accuracy values are not specified. The study reports that multi-class ML classification shows better precision than binary or ternary approaches. However, its limitation is the lack of standardized datasets and uniform evaluation metrics.[1]

Mingchao Qi proposed An Optimized Public Opinion Communication System that uses K-means clustering enhanced with Particle Swarm Optimization (PSO). It uses multiple social-media datasets and reports clustering performance metrics instead of accuracy, achieving improved dissemination depth and sentiment effectiveness. The model demonstrates high purity and reduced SSE through optimized parameters. However, it is limited by the absence of comparative baselines with modern ML or DL classifiers.

Sofie Bergman presented Sentiment Analysis for Emotional Navigation in Written Communication using ML and dictionary-based sentiment methods to aid autistic individuals. The study uses interview-based qualitative datasets, though accuracy is not reported.

It identifies essential design factors for future ML-driven sentiment-support tools. However, its limitation is that no implemented sentiment classifier or measurable performance evaluation is provided.

### 3.3 DEEP LEARNING APPROACHES

Li Yang proposed SLCABG, a deep learning model combining CNN, BiGRU, and attention mechanisms integrated with sentiment lexicons. It uses 100,000 Chinese e-commerce review data from Dangdang and reports significantly improved sentiment classification accuracy (exact value not disclosed). The model captures both local and contextual sentiment features effectively. However, its limitation is the absence of cross-domain evaluation beyond Chinese-language datasets.

Ashagrew Liyih presented a deep learning-based sentiment model using Word2Vec + CNN-BiLSTM for war-related sentiment interpretation. It uses 24,360 labeled YouTube comments and achieves 95.73% accuracy. The approach demonstrates strong performance in multi-class sentiment classification. However, its limitation lies in domain-specific data that may not generalize to other topics or sentiment contexts.

Ou Wu proposed a two-level LSTM approach enriched with lexicon embeddings and a polar-flipping strategy to manage contextual sentiment shifts. It uses three Chinese datasets compiled by the authors and reports superior accuracy compared to SVM, CNN, and LSTM baselines (exact accuracy not provided). The model effectively incorporates negation and polarity changes. However, its limitation is the language dependency and reliance on manual lexicon cues.

In Deep Learning Models for Financial Time Series Forecasting – Cheng Zhang et al. presented a review titled Deep Learning Models for Price Forecasting, examining LSTM, Transformers, GANs, GNNs, and DQNNs. It synthesizes datasets from multiple financial markets, though accuracy figures are not summarized numerically. The review concludes that deep learning drastically improves forecasting over traditional ML approaches. However, the limitation is that no experimental implementation or unified dataset comparison is performed.

### 3.4 HYBRID OR MULTIMODAL & ADVANCED MODELS

A Review and Critical Analysis of Multimodal Datasets for Emotional AI

The authors presented a comprehensive review of multimodal emotional-AI datasets, focusing on methodologies and dataset structures. It synthesizes multiple multimodal datasets without reporting accuracy, as it is not an algorithmic paper. The study identifies requirements for robust multimodal sentiment systems. However, its limitation is that it provides no experimental evaluation or model development.

LGM-HGNN – Heterogeneous Graph Neural Network with Memory (Md. Mithun Hossain) proposed LGM-HGNN, a hybrid of graph neural networks and hierarchical memory modules for aspect-based sentiment analysis. It uses Twitter airline reviews and financial datasets and reports that it outperforms transformer-based baselines, though exact accuracy is not disclosed. The model captures both local and global sentiment dependencies through structured graph relations. However, its limitation is high computational complexity for large graphs.

Liang Yang proposed a dynamic weighted multimodal fusion model using CNNs, attention mechanisms, and genetic-algorithm-based modality weighting. It uses CMU-MOSI, CMU-MOSEI, and CH-SIMS datasets and achieves superior performance across sentiment metrics (accuracy values not specified). The model identifies dominant modalities for each training instance dynamically. However, it is limited by high training overhead and multi-modal synchronization requirements.

Financial Deep Learning Multimodal Review Extension examines hybrid and multimodal deep learning architectures for price forecasting, combining time-series features with sentiment and knowledge-driven signals. The datasets include multiple financial market sources without specific accuracy reporting. It highlights that hybrid DL models outperform traditional and standalone models in complex pattern extraction. However, it lacks unified benchmarking due to heterogeneous dataset characteristics.

***Tabular Summary of Literature Review in Thematic format***

| Title of Paper | Type | Dataset | Methodology | Findings | Limitation |
|---|---|---|---|---|---|
| Natural Language Processing for Sentiment Analysis in Social Media Marketing (Murat Başal) | Traditional NLP Approach | Organizational social-media marketing text (not quantified) | Traditional NLP-based text processing for sentiment extraction | Shows NLP-based sentiment extraction is more reliable than manual analysis | No accuracy, no performance metrics, no comparison with modern ML/DL |
| Conflicting Feelings (Aware) | Traditional conceptual–analytical | Qualitative platform-specific datasets from Aware internal systems | Conceptual and analytical sentiment interpretation | Identifies mismatches between computed and real emotional states | No empirical results or quantitative validation |
| Emotion Analysis of Cross-Media Writing Text (MapReduce Model) | Traditional MapReduce approach | Student internet public-opinion text | MapReduce-based combinatorial sentiment analysis | Improves topic–feature extraction across cross-media formats | Does not use ML/DL; accuracy not reported |
| Sentiment Analysis in Social Media Data for Depression Detection (Babu & Kanaga) | Machine Learning Approach | Social media posts with text, emojis, emoticons | Multi-class ML classification approach | Multi-class ML improves precision over binary models | No standard dataset, no accuracy metrics |
| Optimized Public Opinion Communication | ML+Optimization | Multiple social-media datasets | K-means clustering | Improved sentiment dissemination | No comparison with modern ML/DL classifiers |

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|---|---|---|---|---|---|
| System (Mingchao Qi) | | | enhanced with PSO | depth, higher purity, lower SSE | |
| Optimized Public-Opinion Sentiment Dissemination Model (Qi) | ML+Optimization | Social-media network datasets | K-means + PSO hierarchical dissemination model | Strong dissemination depth; stable polarity patterns | No linguistic or deep-learning integration |
| Sentiment Analysis for Emotional Navigation (Sofie Bergman) | ML + Dictionary-based | Interview-based qualitative datasets | ML + dictionary-based sentiment assistance model | Identifies design needs for ML-supported emotion tools for autistic individuals | No classifier implementation; no measurable accuracy |
| SLCABG (Li Yang) | Deep Learning | 100,000 Chinese e-commerce reviews (Dangdang) | CNN + BiGRU + Attention + Sentiment Lexicon Integration | High sentiment accuracy; learns local + contextual features | No cross-domain evaluation; only Chinese dataset |
| Word2Vec + CNN-BiLSTM War Sentiment (Ashagrew Liyih) | Deep Learning | 24,360 labeled YouTube comments | Word2Vec embeddings + CNN-BiLSTM | Achieves 95.73% accuracy, strong multi-class sentiment performance | Domain-specific, may not generalize |
| Two-level LSTM with Lexicon Embeddings (Ou Wu) | Deep Learning | Three Chinese sentiment datasets | Two-level LSTM + lexicon embeddings + polarity flipping | Outperforms SVM, CNN, LSTM; handles polarity shifts well | Language-dependent; relies on manual lexicon cues |
| Deep Learning Models for Financial Time Series Forecasting (Cheng Zhang et al.) | Deep Learning Review | Multiple financial-market datasets | Review of LSTM, Transformers, GANs, GNNs, DQNNs | DL models outperform traditional ML in price forecasting | No unified experiments; no accuracy summary |
| Bi-LSTM + OCC Cognitive System (Zhuqing Yang et al.) | Deep Learning | University microblog dataset | Bi-LSTM + cognitive affective rule system | Better accuracy than SVM, CNN, LSTM; strong psychological pattern recognition | Dataset limited to university domain |
| Multimodal Emotional-AI Datasets Review | Hybrid / Multimodal Review | Multiple multimodal datasets | Systematic review of multimodal dataset structures | Identifies essential requirements for multimodal sentiment systems | No experimental evaluation or new model |
| LGM-HGNN (Md. Mithun Hossain) | Hybrid Graph Neural Network | Twitter airline reviews, financial datasets | Heterogeneous GNN + hierarchical memory modules | Outperforms transformer baselines; captures global/local sentiment | High computational complexity |
| Dynamic Weighted Multimodal Fusion (Liang Yang) | Multimodal Hybrid (CNN + Attention + GA) | CMU-MOSI, CMU-MOSEI, CH-SIMS | CNN + Attention + Genetic Algorithm weighting | Superior performance; dynamic modality weighting | High training cost; complex synchronization |
| KuDA – Knowledge-Guided Dynamic Attention (Xinyu Feng) | Multimodal Hybrid DL | Four multimodal sentiment datasets | Knowledge-guided dynamic attention fusion | Achieves state-of-the-art performance | Depends on predefined knowledge sources; costly |
| Dynamic Fusion Architecture (Liang Yang) | Advanced Multimodal DL | Standard multimodal datasets | Semantic enhancement + modality-specific feature extraction | Enhances intra-modality understanding before fusion | No comparison with newer transformer architectures |
| Financial Deep Learning Multimodal Review (Hybrid DL) | Hybrid / Multimodal Review | Multiple financial market datasets | Fusion of time-series signals + sentiment + knowledge features | Hybrid DL models outperform standalone models | No unified benchmark; heterogeneous datasets |

## III. RESEARCH GAPS AND FUTURE SCOPE

### 3.1 Latest Deep Learning Approaches

Despite good results from modern deep learning systems like CNN–BiGRU, LSTM variations, or attention setups, their ability to work across different areas is weak - particularly if training relies on data from just one language or subject. Many papers skip consistent measurement methods while failing to test models on shared benchmarks, making it hard to replicate findings. These networks often misread sarcastic tones, indirect emotions, or mixed-language inputs; issues that are still open problems. In addition, few researchers examine how well models handle distorted or manipulated input texts. Without testing in live environments, we can't fully trust their real-life usefulness.

### 3.2 Latest Hybrid and Multimodal Approaches

While hybrid approaches improve sentiment recognition, they demand heavy computing power - so scaling to big or live data becomes tough. Today's multimodal techniques struggle to align inputs from different sources, especially when some data is missing, which weakens real-life performance. A number of these models lack clear explanations, so it's hard to see how each input affects results. On top of that, consistent testing standards are absent, making system comparisons across areas unreliable. In the end, many studies ignore cultural and language differences, limiting worldwide use.

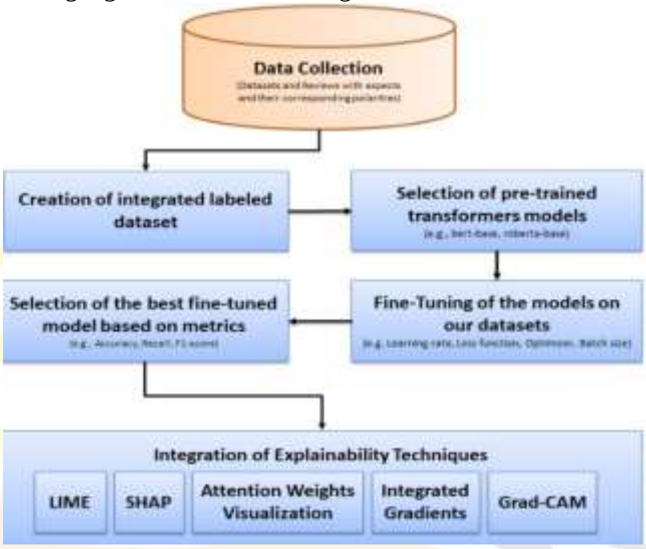


*Fig 5: future trends*

### 3.4 Future Scope

Future research can focus on developing cross-domain and cross-lingual sentiment models that generalize well across diverse languages, cultures, and application areas. There is significant potential in creating lightweight deep learning models optimized for real-time analysis on mobile and edge devices. Multimodal sentiment systems can be enhanced by designing robust fusion strategies that handle missing, noisy, or asynchronously captured data. Future work should also explore explainable and transparent sentiment frameworks to improve trustworthiness in healthcare, finance, and governance applications. Integrating large language models (LLMs) with traditional sentiment pipelines can further enhance contextual understanding and reduce annotation requirements. Additionally, establishing standardized benchmark datasets and evaluation protocols will improve comparability and reproducibility across studies. Finally, incorporating adversarial robustness and bias mitigation techniques can ensure fair and reliable sentiment analysis in real-world deployments.

The final stage of the systematic review involved synthesizing the findings from the 22 selected studies to identify dominant trends, methodological patterns, application contexts, and recurring limitations in sentiment and emotion analysis on social media. The results indicate a clear evolution of analytical approaches over the past decade, moving from lexicon-based and traditional machine learning models toward deep learning architectures and transformer-based frameworks. Most of the reviewed studies employed supervised learning methods, with a growing number integrating hybrid approaches that combine linguistic features, sentiment lexicons, and neural embedding to improve accuracy and contextual understanding.

Twitter emerged as the most frequently analyzed platform due to its large volume of real-time data, public accessibility, and relevance during events such as elections, crises, and public health emergencies. Other platforms such as Facebook, Instagram, SnapChat, and product-review websites appeared in several studies but with less intensity and dataset diversity. Applications of sentiment and emotion analysis were broad, spanning disaster response, mental-health monitoring, competitive market intelligence, political opinion mining, and social behavior prediction. Across studies, emotion detection tasks often proved more challenging than sentiment polarity classification due to the complexity and ambiguity of emotional expression in short-text formats.

Overall, the synthesized findings provide a structured understanding of current research directions and underline the importance of developing robust, ethical, and context-aware sentiment analysis systems capable of operating effectively within the rapidly evolving landscape of social media.

### 3.5 Challenges and Opportunities in Social Media Sentiment Analysis and AI

The growing integration of artificial intelligence in analyzing social media sentiment presents a transformative yet complex landscape [1][4][11][17]. Several challenges arise due to the dynamic, unstructured, and multimodal nature of social media data [6][7][16]. One major challenge is the linguistic variability in online communication, where slang, abbreviations, emojis, code-mixing, and rapidly evolving trends make sentiment detection difficult [1][2]. Sarcasm, irony, and humor remain persistent problems for even advanced models, as they require contextual, cultural, and social cues that are not always explicitly stated [3][14]. Additionally, misinformation, bot-generated content, and coordinated manipulation campaigns distort genuine sentiment signals, affecting model reliability and bias [11].

The demographic and cultural diversity of users introduces further challenges: sentiment expressions vary across regions, languages, and communities, creating domain adaptation issues [6]. Ethical concerns also emerge, particularly related to privacy, surveillance, algorithmic bias, and the potential misuse of sentiment insights for political targeting or psychological profiling. The scale and velocity of data streams demand high computational resources, real-time processing capabilities, and robust filtering mechanisms [10][18].

## IV. CONCLUSION

This systematic review highlights the rapid advancements and growing significance of sentiment analysis and emotion detection across social media platforms. The synthesis of the selected studies demonstrates a clear methodological progression—from lexicon-based techniques and traditional machine learning classifiers to sophisticated deep learning architectures and transformer-based models capable of capturing nuanced emotional expressions. Twitter remains the dominant platform for empirical research, driven by its real-time, high-velocity content and public accessibility, while other platforms such as Facebook, Instagram, SnapChat, and e-commerce reviews provide complementary contexts for understanding user attitudes and behaviors.

Across applications ranging from disaster response and political forecasting to mental-health assessment and competitive market intelligence, sentiment analysis has proven to be a powerful tool for extracting actionable insights from unstructured social data. However, the results also reveal persistent challenges, including data sparsity, language diversity, multimodal complexity, sarcasm detection, and ethical concerns surrounding privacy, transparency, and potential algorithmic biases. These limitations underscore the need for more robust datasets, culturally adaptive models, cross-platform evaluation frameworks, and responsible AI practices. Overall, the findings indicate that while sentiment and emotion analysis on social media has matured substantially, the field continues to evolve in response to emerging data modalities, societal needs, and technological innovations. Future research should prioritize multimodal fusion, explainable AI approaches, and ethically aligned frameworks to ensure that sentiment analysis not only enhances analytical capability but also supports safe, fair, and meaningful applications across diverse social media environments.

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