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Article

SENTIMENT ANALYSIS IN SOCIAL MEDIA: HOW DATA SCIENCE IMPACTS PUBLIC OPINION KNOWLEDGE INTEGRATES NATURAL LANGUAGE PROCESSING (NLP) WITH ARTIFICIAL INTELLIGENCE (AI)

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ABSTRACT
This systematic literature review investigates the advancements, methodologies, challenges, and application domains of sentiment analysis with a particular focus on informal digital text such as social media content. A total of 91 peer-reviewed articles published between 2010 and 2024 were carefully selected and analyzed using the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework to ensure methodological rigor, transparency, and reproducibility. The review spans traditional machine learning algorithms, deep learning models, and transformer-based architectures, examining their role in enhancing sentiment classification accuracy across various textual and multimodal inputs. Key themes emerging from the analysis include the evolution of multimodal sentiment analysis incorporating emojis, images, and videos; the growing focus on emotion classification beyond polarity detection; and the development of multilingual and cross-lingual sentiment systems that aim to extend sentiment mining beyond English-dominated datasets. Furthermore, a notable subset of studies addressed the complexities of detecting sarcasm, irony, and linguistic ambiguity, highlighting significant limitations in even the most advanced models. The review also discusses the growing body of research in financial, political, and health-related sentiment analysis, where domain-specific customization has proven critical for reliable prediction. Despite technical progress, challenges remain in areas such as data imbalance, inconsistent evaluation metrics, lack of cross-domain generalizability, and insufficient attention to ethical concerns, including algorithmic bias and explainability. This review contributes a synthesized and critical understanding of the current state of sentiment analysis and identifies key research gaps, offering a valuable reference point for scholars, developers, and practitioners aiming to improve the robustness, inclusivity, and ethical grounding of sentiment analysis systems.

KEYWORDS
Sentiment Analysis; Natural Language Processing (NLP); Artificial Intelligence (AI); Social Media Analytics; Public Opinion Mining;

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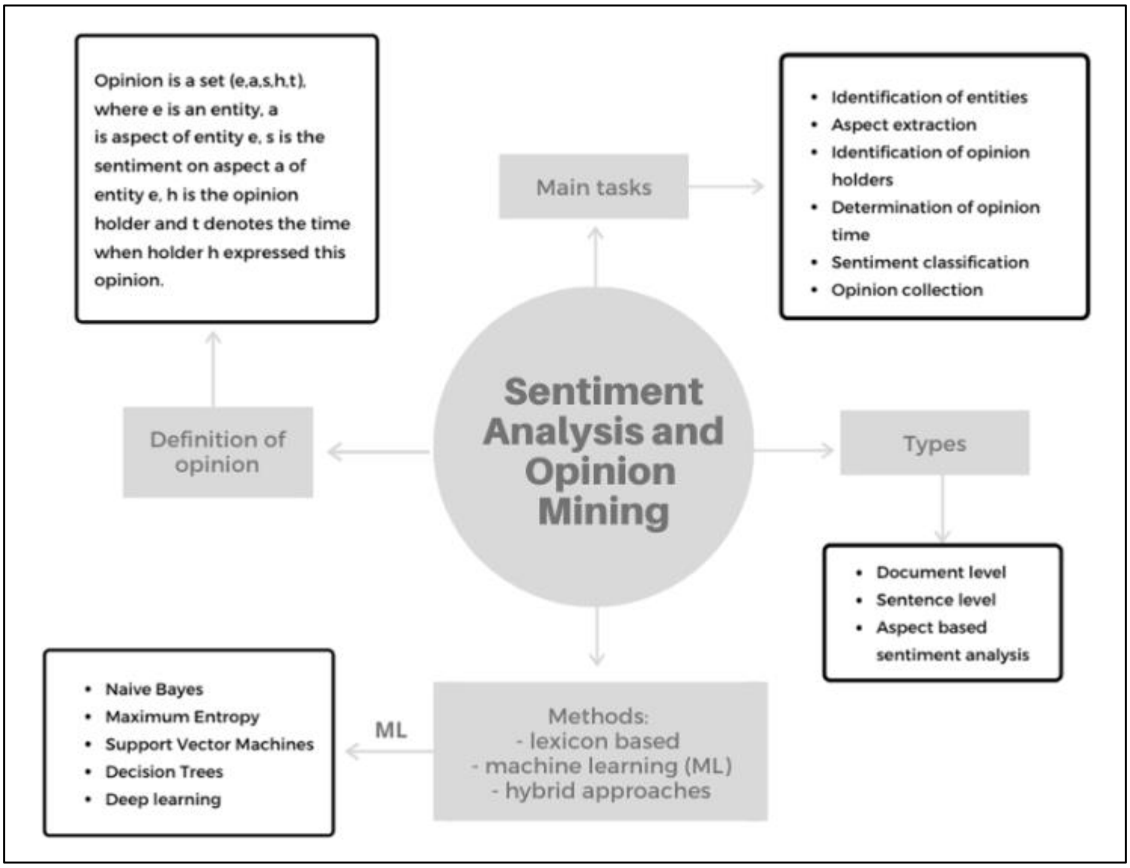
INTRODUCTION

The proliferation of social media platforms such as Twitter, Facebook, Instagram, and Reddit has created a transformative landscape for communication and public discourse (Thara & Poornachandran, 2022). These platforms have evolved into dynamic arenas where individuals express opinions, share experiences, and engage with sociopolitical events in real time. As a result, vast quantities of unstructured text data are generated daily, offering a valuable resource for analyzing public opinion (Dijck & Poell, 2018). The unfiltered and spontaneous nature of social media interactions makes them particularly insightful for gauging sentiment across diverse populations and contexts (Weller, 2016). This deluge of textual information has positioned social media as a central focus in computational linguistics and data-driven decision-making research. Furthermore, sentiment analysis, also known as opinion mining, has emerged as a core technique in interpreting emotional and subjective content in textual data. By leveraging computational methods, sentiment analysis categorizes text into positive, negative, or neutral sentiments (Bose et al., 2019). Traditional machine learning techniques such as Naïve Bayes, Support Vector Machines (SVM), and logistic regression laid the groundwork for early sentiment classification (Yue et al., 2018). However, these models faced challenges in handling the nuances and complexities of natural language, such as sarcasm, idioms, and context-dependent expressions (Ji et al., 2016). These limitations catalyzed a shift toward more sophisticated approaches that integrate Natural Language Processing (NLP) and Artificial Intelligence (AI) to improve semantic understanding and contextual interpretation. Moreover, the integration of NLP with AI has dramatically enhanced the performance and applicability of sentiment analysis across domains. NLP provides the linguistic structure necessary for machines to process and understand human language, while AI, particularly deep learning, empowers models to learn patterns from large datasets (Shah & Shah, 2020).

Figure 1: Sentiment Analysis and Opinion Mining (Source: https://www.alpha-quantum.com)



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According to Dijck and Poell (2018), Neural network architectures such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), including Long Short-Term Memory (LSTM) models, have demonstrated improved accuracy in sentiment detection tasks . Moreover, transformer-based models such as BERT (Bidirectional Encoder Representations from Transformers) have redefined the state of the art in sentiment classification by enabling bidirectional context analysis and pre-training on massive corpora (Yue et al., 2018). Social media sentiment analysis has proven instrumental in various applications, particularly in politics, marketing, and public health. During election cycles, for instance, sentiment trends on Twitter have been used to forecast voter preferences and candidate popularity (Ji et al., 2016). In the commercial sector, companies analyze customer reviews and brand mentions to shape marketing strategies and assess consumer satisfaction (Shah & Shah, 2020). Public health researchers have also employed sentiment analysis to track vaccine hesitancy, monitor mental health trends, and assess public reactions to health crises such as the COVID-19 pandemic (Xu et al., 2022). These studies underscore the critical role that sentiment analysis plays in understanding collective attitudes and responses. Several methodologies underpin the effective execution of sentiment analysis in social media contexts. Preprocessing techniques such as tokenization, stop-word removal, stemming, and lemmatization are fundamental steps that prepare raw text for analysis (Xu et al., 2022; Yue et al., 2018). Feature extraction methods like Term Frequency-Inverse Document Frequency (TF-IDF), word embeddings (Koukaras et al., 2019), and contextual embeddings from transformer models significantly influence the performance of sentiment classifiers (Tabinda Kokab et al., 2022). Evaluation metrics such as accuracy, precision, recall, and F1-score are commonly used to assess the effectiveness of sentiment models across various datasets and languages (Paul et al., 2024; Shah & Shah, 2020; Tabinda Kokab et al., 2022). Challenges in sentiment analysis arise from linguistic diversity, ambiguity, multilingualism, and platform-specific language behaviors such as hashtags, emojis, and abbreviations (Burdisso et al., 2019; Shah & Shah, 2020). Domain adaptation remains a persistent issue, as models trained on one type of data may perform poorly on data from a different domain or context (Pathak et al., 2021). Furthermore, the ethical implications of analyzing user-generated content—particularly issues surrounding privacy, informed consent, and algorithmic bias—have gained attention in recent years (He et al., 2022; Tabinda Kokab et al., 2022; Xu et al., 2022). These challenges highlight the need for robust frameworks and transparent methodologies in the practice of social media sentiment analysis. The theoretical foundations of sentiment analysis are supported by interdisciplinary research spanning computer science, linguistics, psychology, and communication studies. The emotional valence theory, for instance, provides a psychological basis for categorizing sentiments, while computational semantics offers a structural approach to modeling meaning (Abdelfatah et al., 2017). The synergy between these disciplines has led to the creation of lexicons such as SentiWordNet, AFINN, and VADER, which serve as critical resources for sentiment polarity identification (Paltoglou & Thelwall, 2012). These resources, combined with AI-powered analytical frameworks, enable the scalable and real-time processing of public sentiments, enhancing understanding across a wide array of social and commercial phenomena. To objectively explore the role of data science in sentiment analysis for public opinion mining on social media, this study conducts a systematic literature review (SLR) grounded in a transparent, reproducible methodology. The primary objective is to identify, evaluate, and synthesize peer-reviewed research that integrates Natural Language Processing (NLP) and Artificial Intelligence (AI) for sentiment detection across major social platforms. Following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework, this review systematically collects articles published between 2010 and 2024 from digital databases such as Scopus, Web of Science, IEEE Xplore, and ACM Digital Library. The inclusion criteria target empirical studies, methodological advancements, and applied research focusing on social media sentiment analysis that leverages NLP and AI technologies. The review aims to categorize dominant approaches, assess model performance, and reveal research gaps in terms of data preprocessing, algorithm selection, multilingual sentiment handling, and ethical considerations. By synthesizing evidence from interdisciplinary sources, this review establishes a comprehensive understanding of how AI-driven sentiment analysis enhances public opinion knowledge and supports data-informed decision-making.

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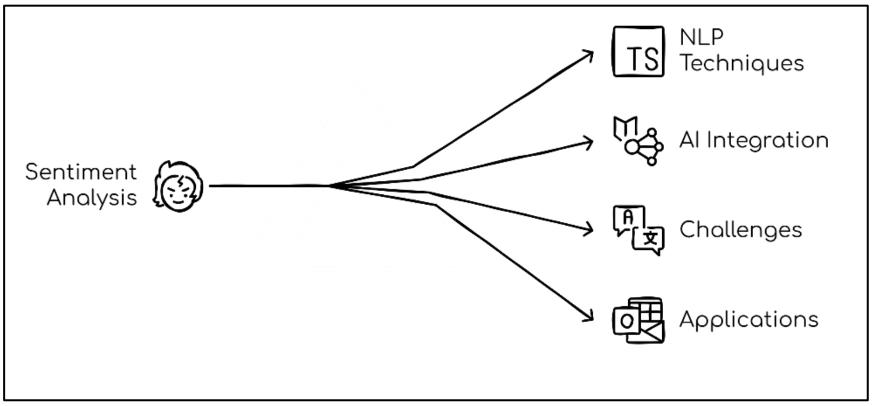
LITERATURE REVIEW

The field of sentiment analysis in social media has undergone rapid evolution, driven by the convergence of Natural Language Processing (NLP), Artificial Intelligence (AI), and Big Data technologies. Understanding public opinion through digital interactions has become an essential focus across disciplines such as political science, marketing, public health, and communication studies. As platforms like Twitter, Facebook, and YouTube continue to generate large volumes of user-generated content, researchers have sought innovative methods to extract sentiment signals embedded in textual, visual, and multimodal data. The use of AI models—ranging from classical machine learning to deep learning and transformer-based architectures—has transformed the scope and scalability of sentiment analysis. This literature review synthesizes findings from peer-reviewed research published over the last decade, highlighting key methodological advancements, emerging techniques, domain-specific applications, and existing challenges. A systematic and thematic categorization approach is applied to classify the literature into distinct areas of focus. By evaluating prior work across multiple dimensions, the review provides a structured understanding of how sentiment analysis technologies are shaping the interpretation of public opinion in the digital era.

Sentiment Analysis

Sentiment analysis, also known as opinion mining, has become a key method in extracting subjective information from text, particularly on social media platforms where users frequently express emotions, opinions, and attitudes (Schouten & Frasincar, 2016). The linguistic complexity and informal nature of social media content necessitate advanced Natural Language Processing (NLP) techniques to interpret sentiment accurately (Hemmatian & Sohrabi, 2017; Ravi & Ravi, 2015). Preprocessing steps such as tokenization, stop-word removal, stemming, and lemmatization are widely used to clean and structure data (Xu et al., 2022). Lexicon-based approaches like SentiWordNet (Ma et al., 2018), AFINN (Gaikwad & Joshi, 2016), and VADER (Wu et al., 2019) assign sentiment polarity scores to words, allowing for simple yet interpretable classification. However, these methods often struggle with sarcasm, negation, and domain specificity (Hassan et al., 2022). As a result, hybrid techniques combining rule-based lexicons with machine learning models have been introduced to mitigate these limitations (Chandrasekaran et al., 2022; Wu et al., 2019).

Figure 2: Exploring the Dimensions of Sentiment Analysis



The integration of Artificial Intelligence (AI), particularly machine learning and deep learning, has significantly enhanced sentiment analysis by enabling scalable and automated processing of social media data (Chandrasekaran et al., 2022; Fengjiao & Aono, 2018). Traditional classifiers such as Support Vector Machines (SVM), Naïve Bayes, and Decision Trees have been employed to classify sentiment with moderate success (do Carmo et al., 2017; Hassan et al., 2022). With the rise of deep learning, models such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks have shown superior performance in capturing long-range dependencies in text (Bai & Yu, 2016; Fu et al., 2011). More recently, transformer-based models like BERT and RoBERTa have outperformed previous architectures by utilizing attention mechanisms and contextual embeddings (Nemes & Kiss, 2020). These models are capable of handling nuanced expressions and have been successfully applied in real-time sentiment tracking (Mansour, 2018). The flexibility and generalizability of these models have allowed researchers to adapt them across a variety of datasets and domains (Hao & Dai, 2016; Mansour, 2018).

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Social media sentiment analysis is complicated by linguistic diversity, slang, emojis, and multilingual content, especially in non-English-speaking regions (Wu et al., 2017; Xiong et al., 2018). Standard sentiment models often underperform in multilingual settings due to cultural and grammatical variations (Zhou et al., 2016). Cross-lingual embeddings and machine translation have been proposed to mitigate these challenges, enabling sentiment analysis across languages using shared semantic spaces (Diamantini et al., 2019). Tools such as LASER, mBERT, and XLM-R have been designed to capture multilingual representations with increasing accuracy (Mansour, 2018). Nonetheless, even with sophisticated models, achieving consistent accuracy across languages and domains remains a methodological obstacle (Hao & Dai, 2016). Moreover, the brevity of posts, the use of hashtags, and the dynamic evolution of online language further compound the issue of generalization and domain adaptation (Hao & Dai, 2016; Md Suhaimin et al., 2023).

Sentiment analysis has found extensive applications across several domains, including political forecasting, brand monitoring, and public health analysis. In political science, Twitter sentiment has been used to analyze public support for candidates and predict election outcomes with notable success (Dhaoui et al., 2017; Nemes & Kiss, 2020). Similarly, marketing research relies on sentiment mining to gauge customer satisfaction and brand loyalty through online reviews and feedback (Hao & Dai, 2016). For instance, sentiment shifts detected in product reviews can serve as early indicators of consumer dissatisfaction (Suhaimin et al., 2023). In the public health sector, social media sentiment analysis has been utilized to assess public response to vaccination campaigns and mental health trends (Dhaoui et al., 2017). During the COVID-19 pandemic, researchers analyzed Twitter sentiment to understand public anxiety, misinformation spread, and compliance with health regulations (Nkomo et al., 2020). These diverse use cases highlight the utility of sentiment analysis in real-time societal monitoring and evidence-based response strategies. Evaluating sentiment analysis models requires robust metrics and benchmarking tools to ensure reproducibility and comparability (Zhao et al., 2014). Commonly used datasets such as the Stanford Sentiment Treebank (SST), IMDb, and Twitter corpora provide standardized platforms for performance testing (Diamantini et al., 2019; Zhao et al., 2014). Evaluation is typically based on metrics like accuracy, precision, recall, F1-score, and area under the curve (AUC) (Hao & Dai, 2016). Beyond technical performance, ethical considerations are gaining prominence, particularly concerning privacy, algorithmic bias, and the potential misuse of sentiment data (Nkomo et al., 2020). Algorithms trained on biased or unbalanced data may reinforce stereotypes or misclassify minority sentiments (Zhao et al., 2014). Furthermore, the unregulated mining of user-generated content raises legal and ethical concerns, especially when sentiments are used for political manipulation or behavioral targeting (Dhaoui et al., 2017; Zhao et al., 2014). These limitations necessitate greater transparency, fairness, and accountability in sentiment analysis research and application.

Role of Data Science and Computational Linguistics in Sentiment Detection

Sentiment detection has evolved at the intersection of data science and computational linguistics, drawing from methods that analyze linguistic patterns and statistical representations to extract emotional valence from text (Deng et al., 2019). Data science provides the infrastructure and computational tools for processing large-scale, high-velocity text data, while computational linguistics contributes the syntactic and semantic rules that guide machine understanding of human language (Hao & Dai, 2016). This interdisciplinary synergy has allowed researchers to uncover insights into user attitudes, emotions, and opinions across platforms such as Twitter, Facebook, and Reddit (Diamantini et al., 2019). Techniques such as part-of-speech tagging, dependency parsing, and named entity recognition have helped ground sentiment classification in grammatical and contextual awareness (Hassan et al., 2013; Nkomo et al., 2020). These approaches are supported by vector space models and statistical representations that convert linguistic features into machine-readable formats for sentiment modeling (Deng et al., 2019; Singla et al., 2017).

Effective sentiment detection relies heavily on feature extraction methods that bridge linguistic theory and data-driven modeling. Term Frequency-Inverse Document Frequency (TF-IDF), n-gram models, and word embeddings such as Word2Vec and GloVe represent early efforts to capture

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context and semantics in sentiment-bearing expressions (Ji et al., 2016; Yue et al., 2018). These tools allow systems to associate sentiment scores with semantically rich patterns rather than isolated keywords (Steiner-Correa et al., 2017). Advanced approaches have adopted contextual embeddings from transformer-based models such as BERT and GPT, offering richer linguistic comprehension by integrating sentence-level context (Kim et al., 2022; Steiner-Correa et al., 2017). Data science enables these linguistic models to scale across massive datasets, facilitating training, validation, and real-time inference (Schouten & Frasincar, 2016). These developments have enabled more nuanced sentiment detection, including polarity, intensity, and emotion classification in noisy and diverse textual inputs (Hemmatian & Sohrabi, 2017).

Figure 3: Types of Sentiment Analysis

Source: www.questionpro.com/ (2024)

Computational linguistics contributes key syntactic and semantic mechanisms that enhance the interpretability and accuracy of sentiment models. Syntax-based sentiment analysis benefits from parsing techniques that identify sentence structure, dependency relations, and grammatical mood—essential for disambiguating sentiment in complex or compound sentences (Xu et al., 2022; Yue et al., 2018). Semantic analysis allows sentiment detection systems to capture word meaning and relationships, improving performance on polysemous terms or implicit sentiment expressions (Ma et al., 2018; Schouten & Frasincar, 2016). Pragmatic aspects, including sarcasm, negation, and figurative language, have been addressed through rule-based and machine learning-enhanced models that account for discourse-level context (Ravi & Ravi, 2015). These linguistic theories are operationalized using data science workflows that incorporate labeled corpora, annotated datasets, and algorithmic validation pipelines (Ma et al., 2018). Together, these components enable the alignment of computational models with natural language phenomena central to human expression and social interaction (Chiarello et al., 2020; Feldman, 2013).

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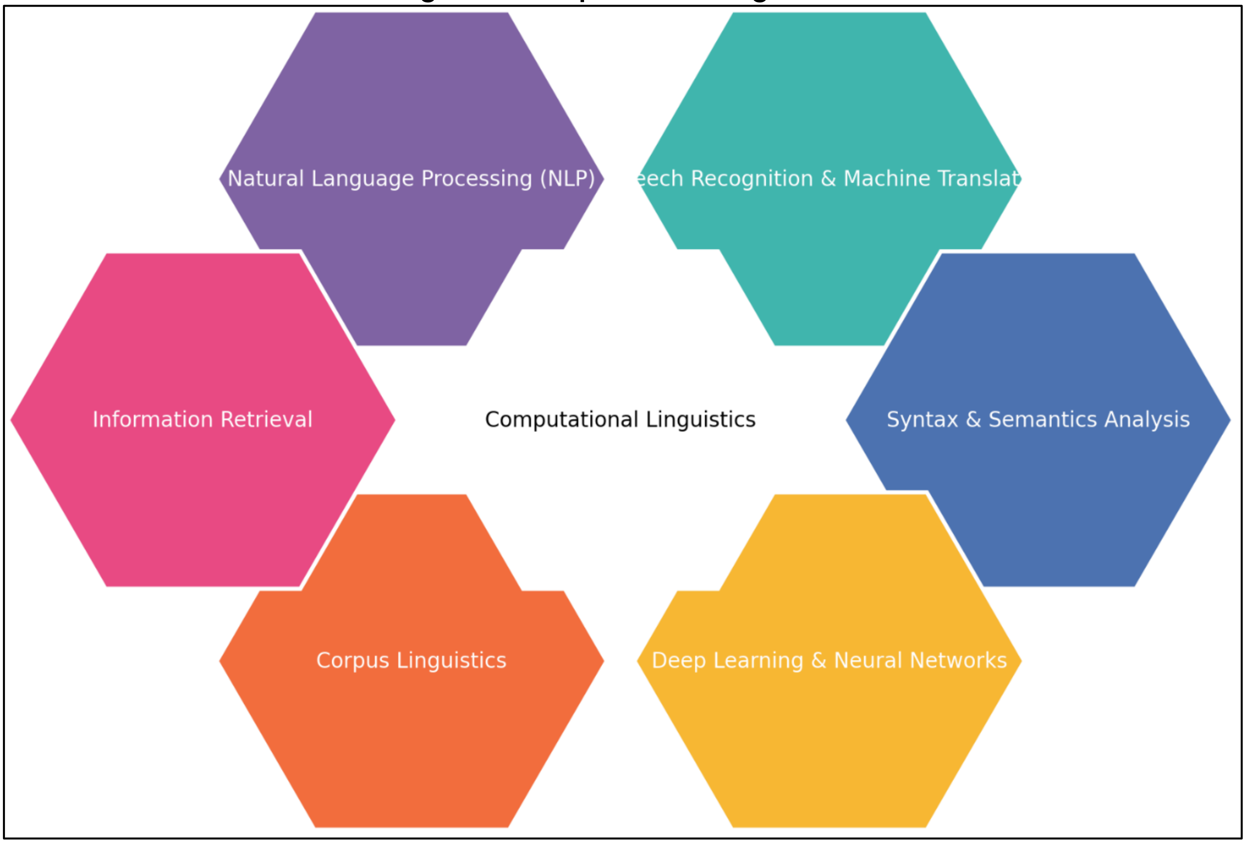
Figure 4: Computational Linguistics

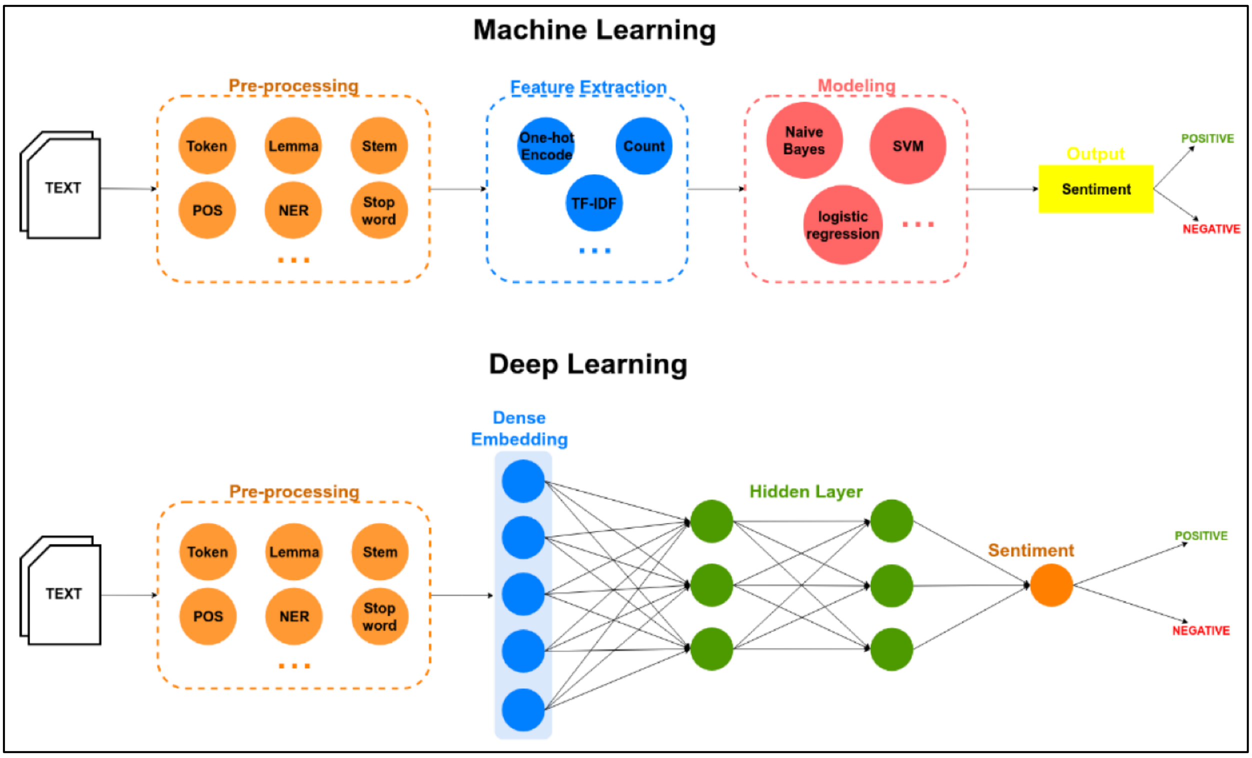


Data science has enabled the deployment of machine learning algorithms capable of processing and learning from vast quantities of linguistically annotated data. Supervised learning models like Naïve Bayes, SVM, and Random Forests have long been applied to sentiment classification tasks due to their simplicity and interpretability (Vinoth & Prabhavathy, 2022). These models have been enhanced by ensemble techniques and neural architectures, including LSTM and GRU networks, which model temporal dependencies and sequential information critical in language processing (Chaudhari et al., 2021). The convergence of these models with computational linguistics allows the encoding of grammatical dependencies and sentence structure into feature representations (Dangi et al., 2022; Gaikwad & Joshi, 2016). Transfer learning and pre-trained language models, particularly BERT, RoBERTa, and XLNet, have further enabled fine-tuned sentiment detection across tasks and domains (Billah & Hassan, 2019). Data science frameworks facilitate this learning process by supporting hyperparameter tuning, performance benchmarking, and model interpretability (Sanoussi et al., 2022). Beyond textual data, sentiment detection has expanded into multimodal analysis, integrating visual, audio, and textual cues to enhance accuracy. Social media content often includes images, emojis, memes, and videos that supplement or contradict textual sentiment, creating complex interpretive scenarios (Sharma & Sharma, 2020). Data science methodologies such as multimodal fusion and late-stage integration models have been used to process and combine different data types (Ayyub et al., 2020). Computational linguistics enables alignment of spoken or written language with visual cues, particularly in emotion recognition and opinion polarity tasks (Sanoussi et al., 2022). Moreover, contextual understanding, including hashtag sentiment (Kumar et al., 2020) and emoticon polarity (Aljarah et al., 2020), is facilitated through linguistically enriched sentiment dictionaries and contextual embedding tools. These approaches are embedded in data-driven pipelines that normalize inputs, apply multimodal classifiers, and evaluate outputs across heterogeneous datasets (Chin et al., 2018). Together, data science and computational linguistics extend sentiment detection into richer, real-world social interactions.

Natural Language Processing Techniques in Social Media Sentiment Analysis

Preprocessing is a foundational step in Natural Language Processing (NLP) that enhances the quality of social media data for sentiment analysis by reducing noise and standardizing input (Nguyen & Shirai, 2015). Given the informal and irregular nature of social media content, including abbreviations, emojis, misspellings, and slang, techniques such as tokenization, stemming, lemmatization, stop-word removal, and normalization are essential (Zadeh et al., 2017). Emoji and emoticon normalization has also played a role in sentiment detection, with emoji lexicons helping capture emotional nuances (Cai & Xia, 2015). Hashtag segmentation and URL filtering have been integrated to isolate sentiment-bearing terms (Ruder et al., 2016; Wang et al., 2016). These techniques have enabled improved text representation and model training, particularly when used in conjunction with domain-specific corpora (Poria et al., 2015).

Figure 5: Differences between two classification approaches of sentiment polarity, machine learning (top), and deep learning (bottom).



Lexicon-based methods have been widely used in social media sentiment analysis due to their simplicity and interpretability. These approaches use predefined dictionaries of words associated with sentiment scores, including popular lexicons such as SentiWordNet (Yu et al., 2017), AFINN (Nguyen & Shirai, 2015), and VADER (Wang et al., 2018). Lexicon-based methods have shown reliable results in short-form texts like tweets and Facebook posts, particularly when context-independent word-level sentiment is sufficient (Ruder et al., 2016; Wang et al., 2018). However, limitations arise when handling sarcasm, irony, context ambiguity, and negation (Nguyen et al., 2020; Zadeh et al., 2017). Hybrid approaches combining lexicons with machine learning classifiers have emerged to mitigate these issues, offering improved performance without sacrificing interpretability (Barbieri et al., 2020; Ghosal et al., 2019). Lexicon adaptability across languages and domains has also been a subject of research, with multilingual lexicons designed for sentiment mining in cross-cultural contexts (Poria et al., 2015). Feature extraction has been central to transforming text into structured representations suitable for machine learning. Techniques such as bag-of-words (BoW), n-gram modeling, and Term Frequency-Inverse Document Frequency (TF-IDF) have been widely employed in early sentiment classification systems (Wang et al., 2018; Yu et al., 2017). While these methods capture surface-level term occurrence and co-occurrence, they lack the semantic depth needed for nuanced sentiment detection (Zadeh et al., 2017).

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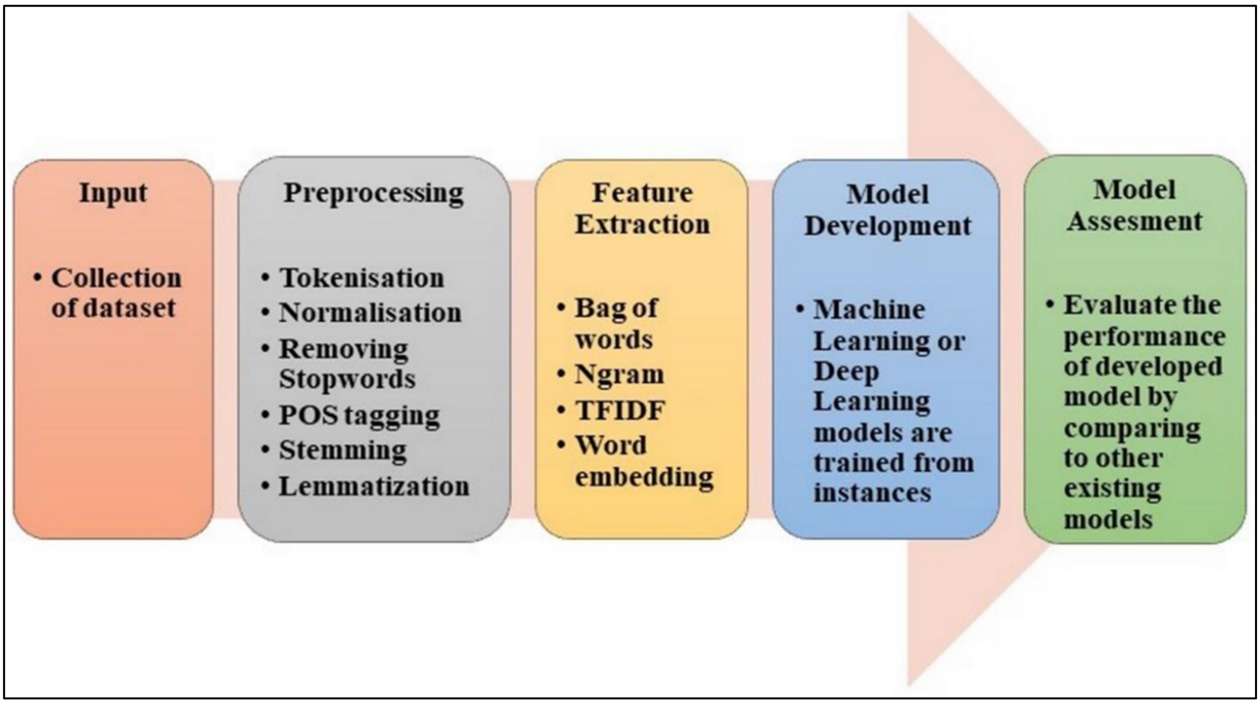
Advanced methods such as latent semantic analysis (LSA) and topic modeling via Latent Dirichlet Allocation (LDA) have attempted to capture hidden thematic structures (Fu et al., 2011). These approaches have been supplemented by syntactic parsing, dependency trees, and part-of-speech tagging to better represent sentence structure and improve model understanding (Özyurt & Akcayol, 2021). Although widely used, traditional techniques often struggle with context sensitivity and polysemy inherent in informal social media language (Alwakid et al., 2022).
The application of deep learning has transformed NLP tasks by allowing sentiment models to learn hierarchical features from raw text. Recurrent Neural Networks (RNNs), particularly Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) models, have been effective in capturing sequential dependencies and emotional flow in social media text (Sanoussi et al., 2022). Convolutional Neural Networks (CNNs) have also been used to detect sentiment-bearing phrases by learning spatial features across word embeddings (Jhanwar & Das, 2018). More recently, transformer-based architectures like BERT (Bidirectional Encoder Representations from Transformers) have achieved state-of-the-art performance by using self-attention mechanisms and bidirectional context encoding (Akula & Garibay, 2021; Baheti & Kinariwala, 2019). These models have been pre-trained on massive corpora and fine-tuned for sentiment classification tasks, resulting in enhanced performance across benchmark datasets (Konate & Du, 2018; Liu & Chen, 2019). Contextual word embeddings derived from these models outperform static embeddings like Word2Vec and GloVe by accounting for syntactic and semantic variations (Akula & Garibay, 2021; Ghosh et al., 2017). Evaluating NLP-driven sentiment models requires standardized metrics such as accuracy, precision, recall, and F1-score, often benchmarked using datasets like SST, SemEval, and IMDb (Ghosh et al., 2017; Konate & Du, 2018). Challenges persist in handling code-switching, idiomatic expressions, negation, and sarcasm in informal social media text (Liu & Chen, 2019; Thara & Poornachandran, 2022). Sarcasm detection has been explored using contextual modeling and annotation-based corpora, yet remains a difficult task due to its implicit nature (Ghosh et al., 2017). Multilingual NLP for sentiment analysis has attracted interest, with models like multilingual BERT (mBERT) and XLM-R showing cross-lingual generalization capability ((Konate & Du, 2018). However, performance often declines in low-resource languages or culturally diverse corpora, emphasizing the need for robust cross-linguistic tools (Olaniyan et al., 2023). Tools integrating both symbolic and statistical NLP continue to dominate sentiment analysis research, especially when aligned with domain-specific adaptations and labeled datasets (Sanoussi et al., 2022; Baheti & Kinariwala, 2019).

Syntactic and Semantic Analysis in Social Text Mining

Syntactic analysis serves as a crucial element in social text mining by offering structural representations of sentences that aid in understanding relationships between words and phrases. Techniques such as part-of-speech (POS) tagging, constituency parsing, and dependency parsing have been widely adopted to extract syntactic patterns from user-generated content (Fu et al., 2016). POS tagging helps identify the grammatical roles of words, improving the precision of downstream sentiment classification tasks (Behdenna et al., 2018). Dependency parsing, in particular, has been instrumental in detecting modifier-head relationships, which are essential for recognizing negation and intensification (Moraes et al., 2013). Tools such as the Stanford CoreNLP and spaCy have facilitated syntactic analysis in large-scale social media datasets (Gupta et al., 2018; Zhang et al., 2018). In syntactically rich models, sentiment classification accuracy has improved when syntactic features are incorporated alongside lexical ones, especially in handling complex sentence structures (Sanoussi et al., 2022).
Semantic analysis in social text mining goes beyond structural representation to interpret the meaning and context of words, phrases, and sentences. Semantic Role Labeling (SRL) identifies predicates and their associated arguments, enabling better understanding of "who did what to whom" in a sentence (Deters & Mehl, 2012). Word Sense Disambiguation (WSD) further contributes by resolving ambiguity in polysemous words, which is critical for sentiment polarity determination in informal contexts (Sanoussi et al., 2022). In social media analysis, the use of semantic lexicons such as WordNet, SentiWordNet, and ConceptNet has supported the enrichment of sentiment models with semantic features (Ansari et al., 2023). These semantic enhancements are particularly useful in detecting implicit sentiments and context-dependent meanings, which lexicon-only

models often miss (Jhanwar & Das, 2018). Studies applying SRL and WSD report improved sentiment prediction in domains like politics and brand reviews, where language is nuanced and domain-specific (Xia et al., 2011).

Figure 6: Basic steps to perform sentiment analysis and emotion detection



Source: *Nandwani and Verma* (*2021*)

The integration of syntactic and semantic information has been greatly advanced through deep learning models, particularly those designed to capture compositional meaning and context. Recursive Neural Networks (RecNN) and Tree-LSTMs have been applied to parse tree structures, enabling models to understand hierarchical syntactic relationships (Ravi & Ravi, 2016). Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) have demonstrated the ability to model long-distance dependencies in text while incorporating syntactic cues (Al Amrani et al., 2018). Transformer-based models like BERT and RoBERTa, while primarily attention-based, implicitly capture syntactic and semantic information by training on large-scale corpora with masked language modeling objectives (Lei et al., 2016). These models have outperformed traditional classifiers in benchmark sentiment tasks and demonstrated resilience to linguistic complexity (Piana et al., 2014). Hybrid architectures incorporating both parse trees and contextual embeddings have achieved high accuracy in sentiment and emotion detection in Twitter data (Yu et al., 2018).

Syntactic and semantic features are particularly crucial in addressing linguistic phenomena such as sarcasm, irony, and negation—common in social media discourse. Sarcasm detection relies on understanding the incongruity between literal meaning and intended sentiment, which syntactic features alone cannot resolve (Rocktäschel et al., 2015). Semantic analysis, including sentiment-shifting structures and pragmatic context, has been employed to identify sarcastic expressions more effectively (Chaudhari et al., 2021; Rocktäschel et al., 2015). Negation handling remains another core challenge, as it directly alters sentiment polarity. Dependency parsing and scope-based sentiment reversal techniques have been used to detect negation cues and adjust classification outcomes accordingly (Shi, 2019; Yu et al., 2018). Additionally, idiomatic and colloquial expressions require semantic models trained on informal corpora to avoid misclassification (Mitrović et al., 2011). These studies emphasize the importance of jointly modeling syntax and semantics to handle ambiguous sentiment expressions typical of social media

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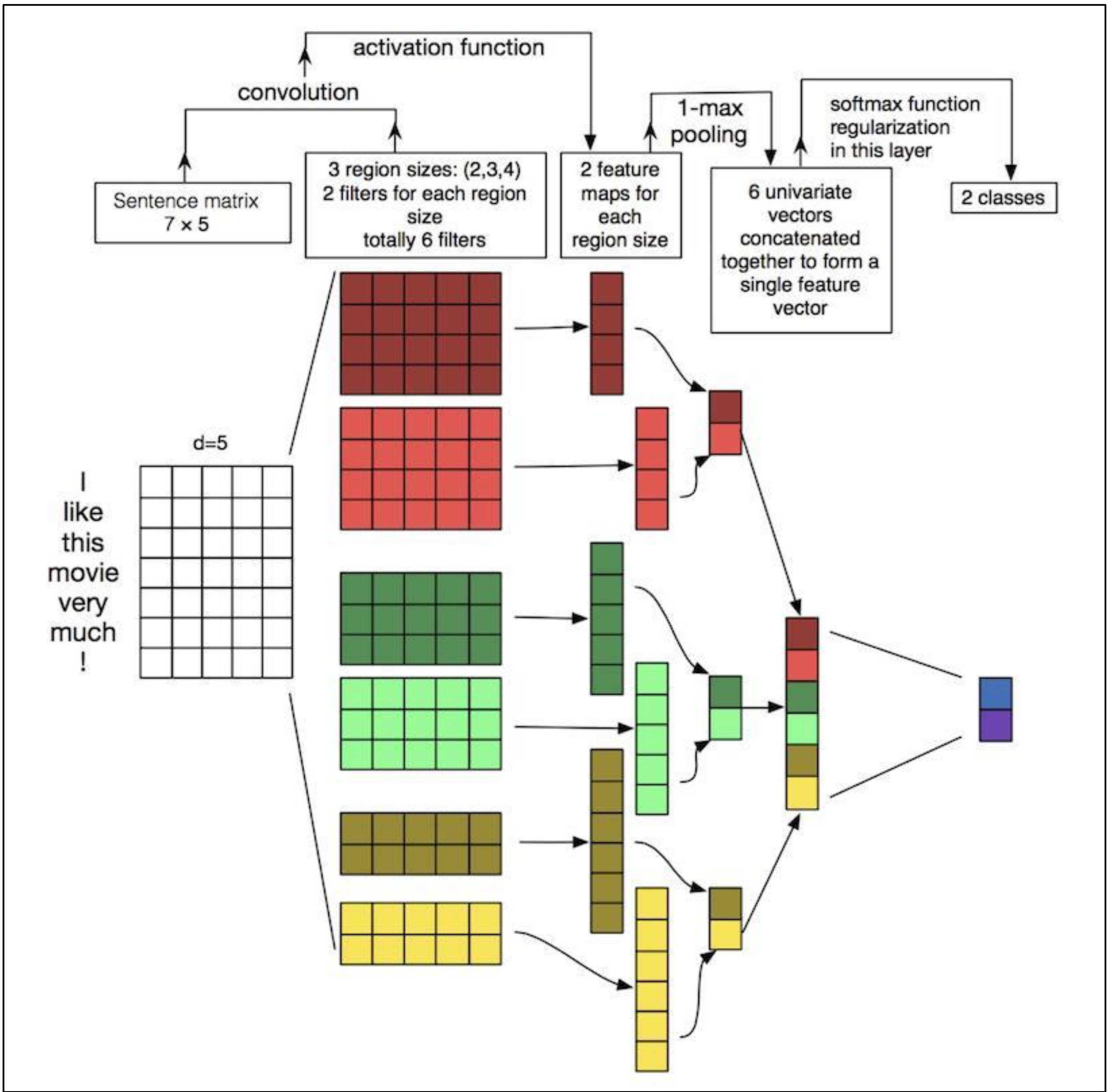
platforms. The effectiveness of syntactic and semantic models in sentiment analysis is often evaluated using benchmark datasets such as the Stanford Sentiment Treebank (Li & Zou, 2024), SemEval datasets (Ravi & Ravi, 2016), and Twitter-specific corpora (Zhang et al., 2022). Metrics such as accuracy, F1-score, and Matthews Correlation Coefficient (MCC) have been used to compare model performance across tasks (Lai et al., 2015). Results show that models integrating syntactic structures and semantic role labeling consistently outperform those relying on surface features alone, particularly in domains with high linguistic variability (Habernal et al., 2015; Yu et al., 2018). However, the portability of such models across domains—e.g., from politics to healthcare—has been limited by vocabulary drift, domain-specific phraseology, and annotation inconsistency (Glorot et al., 2011; Pan et al., 2010). Recent studies have explored domain adaptation techniques using shared embeddings and transfer learning to address these issues (Ruder et al., 2019; Xu et al., 2020).

AI and Machine Learning Models for Sentiment Classification

Traditional machine learning algorithms have laid the foundation for early sentiment classification tasks by providing robust statistical models capable of handling large-scale, high-dimensional text data. Naïve Bayes, Logistic Regression, and Support Vector Machines (SVM) have been extensively used in sentiment analysis due to their simplicity, interpretability, and computational efficiency (Aljarah et al., 2020; Younus et al., 2024). These classifiers rely on numerical feature extraction methods such as bag-of-words (BoW), n-grams, and TF-IDF to transform textual content into vectors (Hossain et al., 2024; Mahabub, Das, et al., 2024; Mahabub, Jahan, et al., 2024; Vinoth & Prabhavathy, 2022). Studies have demonstrated that Naïve Bayes performs particularly well on short-form texts like tweets and product reviews due to its assumption of feature independence and speed in real-time classification scenarios (Ammar et al., 2024; Haidar et al., 2017; Mahfuj et al., 2022; Nalinde & Shinde, 2019). Logistic Regression, known for its probabilistic output, has shown high accuracy in binary sentiment tasks, particularly when combined with linguistic preprocessing steps (Chaudhari et al., 2021; Faria & Rashedul, 2025; Vinoth & Prabhavathy, 2022). Furtherer, the Naïve Bayes algorithm has been widely adopted for sentiment classification tasks on social media platforms due to its speed and low computational cost (Dangi et al., 2022; Dhaoui et al., 2017; Jahan, 2023). In early Twitter sentiment studies, researchers used Naïve Bayes to classify tweets into positive, negative, or neutral categories with considerable success when paired with unigram and bigram features (Ji et al., 2021; Sunny, 2024a, 2024b, 2024c). Despite its strong baseline performance, the algorithm has shown sensitivity to feature sparsity and context loss, especially in complex or ambiguous expressions (Hassan et al., 2017; Rahaman & Islam, 2021; Tonoy & Khan, 2023). Enhancements such as Laplace smoothing, feature selection based on mutual information, and domain-adapted lexicons have been introduced to improve classification performance (Al-Arafat, Kabi, et al., 2024; Gaikwad & Joshi, 2016; Shah & Shah, 2020). Naïve Bayes has also been employed in multilingual sentiment tasks and low-resource environments, where it outperformed more complex models in constrained computational settings (Arafat et al., 2024; Chaudhari et al., 2021; Mohiul et al., 2022; Nahid et al., 2024).

Logistic Regression offers a probabilistic perspective on sentiment classification, making it especially useful in domains where interpretable and explainable models are required (Hassan et al., 2017). This algorithm models the probability that a given instance belongs to a particular sentiment class, facilitating nuanced decision-making in binary or multiclass tasks (Dhaoui et al., 2017; Saif et al., 2017). Logistic Regression has been effectively applied in scenarios with high-dimensional and sparse text data, especially when regularization techniques such as L1 and L2 are used to prevent overfitting (Arafat et al., 2024; Vinoth & Prabhavathy, 2022). In comparative evaluations, Logistic Regression has performed competitively against Naïve Bayes, particularly in applications involving structured datasets and domain-specific vocabularies (Bhuiyan et al., 2024; Lin & Kolcz, 2012). The algorithm's compatibility with various vectorization methods—including TF-IDF, word embeddings, and sentiment lexicons—has enabled its adoption across multiple platforms and languages (Chen et al., 2022; Chowdhury et al., 2023). Moreover, Support Vector Machines (SVM) have consistently demonstrated high performance in sentiment classification due to their ability to maximize the margin between classes and handle non-linear separability using kernel tricks (Shah & Shah, 2020). Studies have shown that SVM outperforms Naïve Bayes and Logistic Regression in handling high-dimensional textual data, especially when using linear and RBF kernels (Gaikwad & Joshi, 2016). In Twitter sentiment analysis, SVM has proven robust against noisy and imbalanced data, often achieving higher F1-scores in benchmark tasks (Hassan et al., 2017). Its integration with feature selection methods, such as chi-square and information gain, further enhances its discriminative power (Chen et al., 2022). Additionally, ensemble techniques combining SVM with rule-based or lexicon-assisted models have shown improvements in precision, particularly in sentiment-rich domains like finance and health (Chaudhari et al., 2021).

Figure 7: A Sensitivity Analysis of Convolutional Neural Networks for Sentence Classification



Source: Zhang and Wallace (2015)

Empirical comparisons across datasets such as SST, IMDb, and Twitter corpora have illustrated that while Naïve Bayes, Logistic Regression, and SVM remain strong baselines, their performance is sensitive to feature engineering, domain context, and preprocessing quality (Chen & Zhang, 2018; Mohiul et al., 2022). SVM generally offers superior performance in classification tasks with complex decision boundaries, whereas Naïve Bayes maintains efficiency in real-time and short-text analysis

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(Al-Arafat, Kabir, et al., 2024; Wei et al., 2021; Xu et al., 2019). Logistic Regression stands out for its interpretability and probabilistic outputs, making it suitable for explainable AI applications (Mohiul et al., 2022; Yan et al., 2016). However, traditional models often struggle with nuanced linguistic phenomena such as sarcasm, negation, and idiomatic expressions, which require deeper contextual understanding (Hossen et al., 2023; Zhang et al., 2022). Despite these limitations, these algorithms continue to be used as reliable benchmarks in sentiment analysis research and are frequently integrated into hybrid systems for improved effectiveness (Roksana, 2023; Zhai & Zhang, 2015; Zhang et al., 2011).

Deep Learning Models: CNN, RNN, LSTM, and GRU

Deep learning has transformed sentiment analysis by enabling models to learn hierarchical and contextual representations of textual data without manual feature engineering. Unlike traditional models that depend on sparse representations, deep learning architectures such as Convolutional Neural Networks (CNN), Recurrent Neural Networks (RNN), Long Short-Term Memory networks (LSTM), and Gated Recurrent Units (GRU) extract semantic and syntactic patterns from sequences, improving classification accuracy (Sabid & Kamrul, 2024; Usama et al., 2019). These models have been applied effectively to large-scale social media datasets, offering superior performance in handling informal, noisy, and unstructured text common on platforms like Twitter and Reddit (Aklima et al., 2022; Munira, 2025; Usama et al., 2019; Zhou et al., 2020). Their ability to learn from sequential context and capture deep feature dependencies has made them suitable for sentiment-rich applications such as emotion recognition, stance detection, and opinion mining (Jim et al., 2024; Rojas-Barahona, 2016; L. Zhang et al., 2018). Moreover, CNNs, originally designed for image recognition, have been successfully adapted to NLP tasks, particularly for detecting local patterns in text such as sentiment-bearing n-grams (Aklima et al., 2022; Kastrati et al., 2021). By applying convolutional filters over word embeddings, CNNs can capture spatial dependencies and position-invariant features relevant for sentiment classification (Badjatiya et al., 2017; Khatun et al., 2025; Zhang et al., 2018). Studies have shown that CNNs perform well on short texts like tweets or product reviews, where localized patterns such as negation, intensifiers, or sentiment modifiers play a central role (Rojas-Barahona, 2016). When combined with max-pooling and dropout, CNNs generalize effectively and mitigate overfitting in sparse textual datasets (Hasan et al., 2024; Khan, 2025; L. Zhang et al., 2018). CNN-based sentiment models have outperformed traditional machine learning classifiers on benchmark datasets including SST, IMDb, and Amazon reviews (Tang et al., 2015). Moreover, RNNs are particularly suitable for sentiment analysis due to their capacity to handle sequential data and preserve information across time steps (Mukherjee, 2019). They have been employed in text classification tasks where word order and context significantly impact sentiment orientation (Zhang et al., 2018). However, standard RNNs suffer from vanishing gradient problems, limiting their ability to model long-term dependencies (Mukherjee, 2019). Despite this limitation, RNNs have achieved notable results in short-sequence sentiment tasks when trained on sufficient data and integrated with pre-trained embeddings like Word2Vec or GloVe (Badjatiya et al., 2017). Bidirectional RNNs (Bi-RNNs) have been proposed to capture both past and future context, further improving sentiment classification in domains like political discourse and customer reviews (Rojas-Barahona, 2016).

LSTM networks address the limitations of traditional RNNs by incorporating gating mechanisms that enable selective retention and forgetting of information over long sequences (Badjatiya et al., 2017; Zhou et al., 2020). LSTMs have demonstrated state-of-the-art performance in sentiment classification tasks, particularly in capturing sentiment polarity that emerges later in a sentence or paragraph (Subramani et al., 2019; Usama et al., 2019). Studies utilizing LSTM for tweet-level sentiment detection have reported improvements in accuracy, especially in handling sarcasm, negation, and emotionally nuanced expressions (Jamatia et al., 2020; Zhang et al., 2018). Hybrid architectures combining CNNs and LSTMs have further enhanced model performance by capturing both local and sequential patterns in sentiment-laden text (Abbasi et al., 2022; Kastrati et al., 2021). LSTM-based models have been widely validated on datasets such as SemEval, Yelp, and Twitter corpora, where temporal dependencies and complex syntax are prevalent (Usama et al., 2019). Gated Recurrent Units (GRU) offer a simplified architecture compared to LSTM, combining the forget and input gates into a single update gate while maintaining similar

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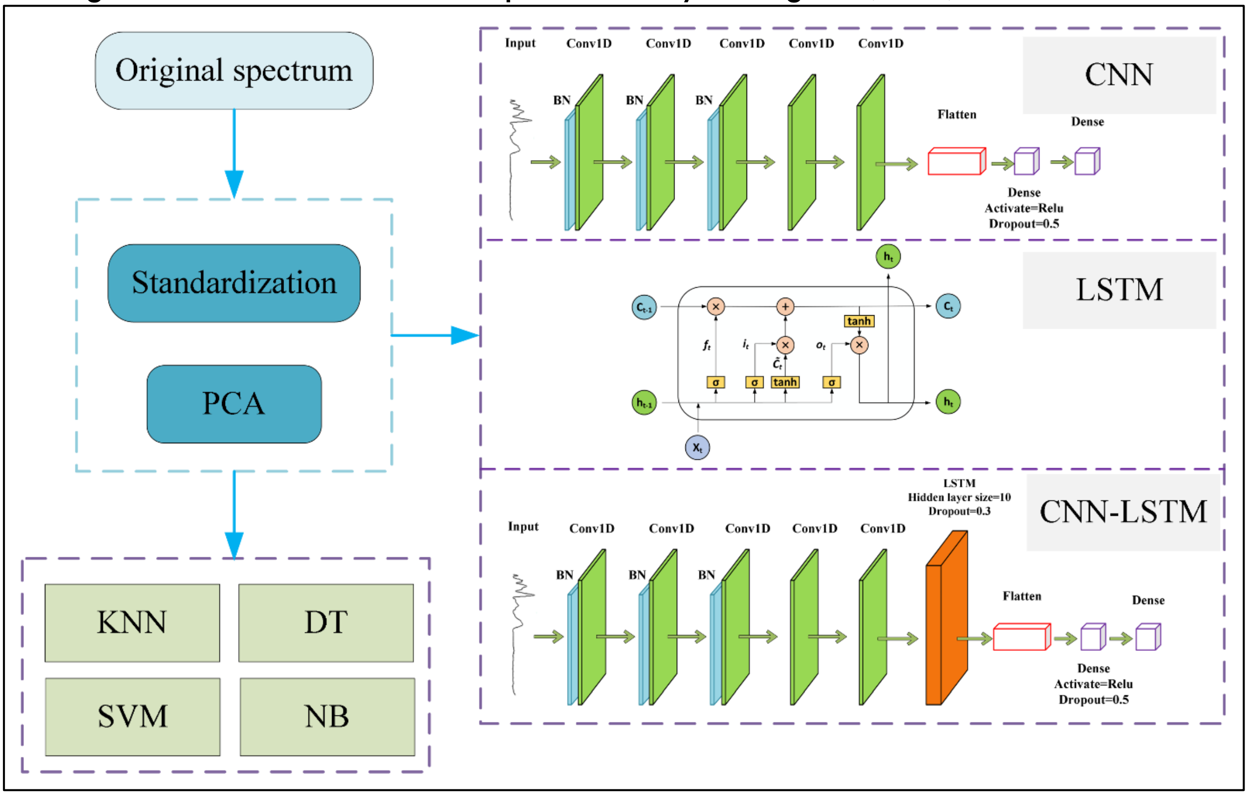
performance in sentiment tasks (Shanmugavadivel et al., 2022; Subramani et al., 2019). GRUs have shown competitive results in both short and long sequence modeling, with reduced computational overhead, making them suitable for real-time social media sentiment applications (Mukherjee, 2019). Studies comparing GRUs and LSTMs have found that GRUs often perform equally well in scenarios with limited training data or constrained resources (Abbasi et al., 2022). Bidirectional GRUs (Bi-GRU) further enhance sentiment prediction by incorporating forward and backward semantic flows, particularly in multilingual or code-mixed data (Abbasi et al., 2022; Badjatiya et al., 2017). GRU models have also been integrated into attention mechanisms to emphasize sentiment-relevant tokens, further refining polarity classification in complex text streams (Jamatia et al., 2020).

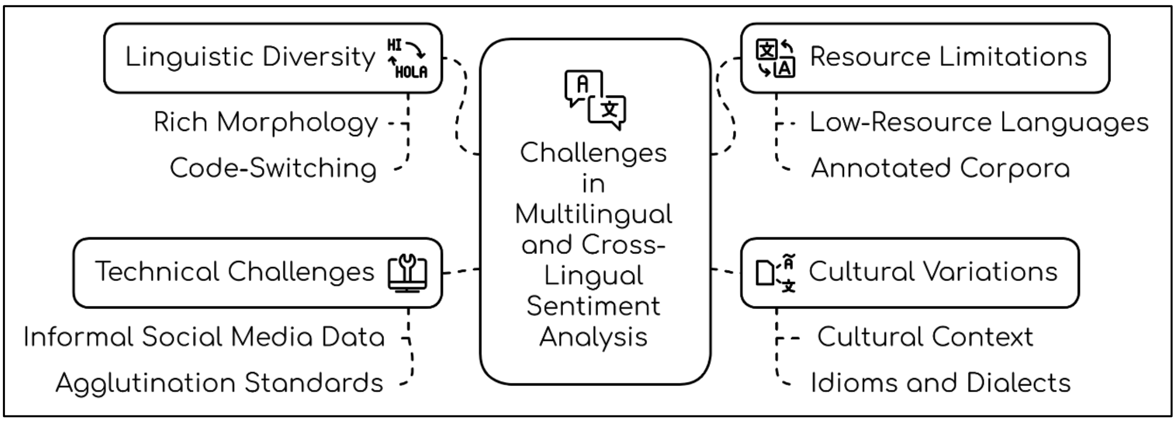
Figure 8: Model Architectures for Spectrum Analysis Using CNN, LSTM, and Classical ML



Source: Zhou et al.*(2023).*

Multilingual and Cross-Lingual Sentiment Analysis

Figure 9: Challenges in Multilingual and Cross-Lingual Sentiment Analysis



Sentiment analysis of non-English and multilingual text presents significant challenges due to linguistic diversity, limited resources, and cultural variations in sentiment expression (Akhtar et al.,

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2017). Languages with rich morphology, such as Arabic, Turkish, and Hindi, complicate tokenization, stemming, and syntactic parsing (Li et al., 2018; Peñalver-Martinez et al., 2014). Many sentiment analysis tools and lexicons are developed primarily for English, resulting in lower performance and transferability to other languages (Arias et al., 2013). Moreover, cultural context affects how sentiment is linguistically encoded, and direct translations often fail to capture sentiment intensity or polarity (Davila et al., 2012). Low-resource languages frequently lack annotated corpora and sentiment lexicons, creating data scarcity issues (Arias et al., 2013; Chaturvedi et al., 2019). Code-switching—where multiple languages are used within a single sentence—also introduces noise and syntactic ambiguity that hinders traditional NLP pipelines (Arias et al., 2013; Peñalver-Martinez et al., 2014). Non-English texts often include idioms, dialects, and informal terms not present in standardized training datasets, which makes sentiment detection inconsistent across languages (Abualigah, 2019). Even within a single language, regional dialects may express sentiment differently, and reliance on literal word-to-word matching can lead to misclassification (Poria et al., 2016). Additionally, multilingual social media content frequently contains emojis, hashtags, and transliterations, which further complicate preprocessing and feature extraction (Li et al., 2018). NLP tools trained on formal text sources like news articles or Wikipedia often perform poorly on informal social media data from diverse linguistic backgrounds (Peñalver-Martinez et al., 2014). The absence of universal tokenization standards across languages adds to inconsistencies in model outputs, especially in agglutinative languages like Finnish or Korean (Chaturvedi et al., 2019). Consequently, researchers have had to adapt or build language-specific models and preprocessing pipelines to ensure contextual accuracy.

Cross-lingual word embeddings and translation-based models have been developed to overcome language barriers in sentiment analysis. Techniques such as bilingual word embeddings, multilingual embeddings (e.g., MUSE, LASER), and contextual models like multilingual BERT (mBERT) and XLM-R have shown promising results in aligning sentiment-bearing words across languages in shared vector spaces (Chaturvedi et al., 2019). These models leverage large-scale corpora to learn language-independent representations that improve performance on low-resource and zero-shot sentiment tasks (Karyotis et al., 2018). Translation-based sentiment models use machine translation to convert non-English texts into English before applying monolingual sentiment classifiers (Phu et al., 2016). While translation can standardize input, it risks semantic distortion and loss of sentiment nuance during conversion (Zhou et al., 2023). Nevertheless, cross-lingual transformer models have demonstrated improved generalization, enabling sentiment transfer across domains and languages with minimal labeled data (Dash et al., 2015).

Benchmark datasets are critical for evaluating multilingual and cross-lingual sentiment models. Resources like the Multilingual Amazon Reviews Corpus (Eke et al., 2021), Twitter Sentiment Corpus for Arabic (Alfina et al., 2017), and the SemEval datasets for multilingual sentiment tasks provide standardized testing grounds for comparative analysis (Gandhi et al., 2023; Sodhi et al., 2021). Additionally, the NoReC dataset for Norwegian (Cojocaru et al., 2022), Hindi-English Code-Mixed Corpus (Sodhi et al., 2021), and various regional corpora for Spanish, French, and German have expanded research into non-English sentiment mining (Gandhi et al., 2023). Language-specific sentiment lexicons such as NRC Emotion Lexicon, FEEL (for French), and OpeNER (for Dutch and Spanish) support semantic annotation across diverse linguistic datasets (Zhang et al., 2022). These resources, combined with open-source NLP toolkits like Polyglot and UDPipe, enable reproducible experimentation in multilingual settings (Chakravarthi et al., 2022).

Cross-lingual and multilingual sentiment models have shown encouraging results on standard benchmarks, but their performance varies depending on data quality, domain specificity, and linguistic complexity. Multilingual BERT (mBERT) and XLM-R, for instance, outperform earlier models in zero-shot transfer tasks but still exhibit biases in lower-resource languages and morphologically rich structures (Sodhi et al., 2021). Evaluation metrics such as macro-F1, accuracy, and confusion matrices are used to assess these models, often revealing that high-resource language pairs like English-Spanish yield stronger performance than English-Amharic or English-Hindi (Zhang et al., 2022). Furthermore, models trained on formal corpora tend to underperform on informal or domain-specific texts such as tweets, customer reviews, or political commentary (Steiner-Correa

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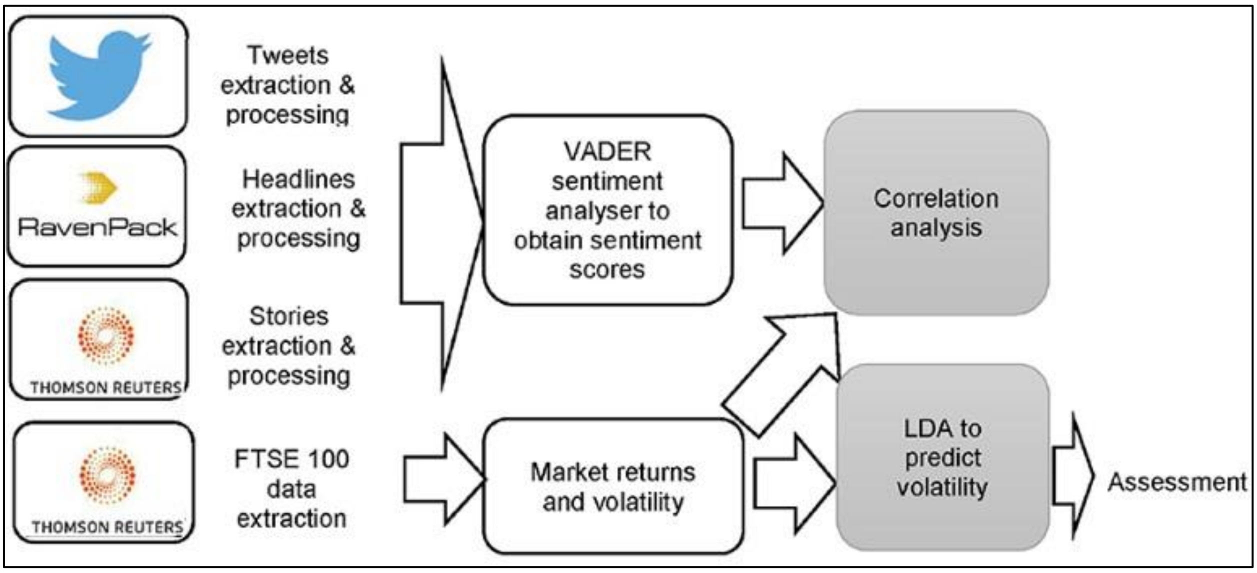
et al., 2017). Domain adaptation strategies, including fine-tuning on language-specific corpora and multi-task learning, have improved performance but require substantial labeled data (He et al., 2022). These variations highlight the need for contextual sensitivity, balanced datasets, and culturally aligned sentiment annotations in multilingual sentiment classification research.

Financial Market Predictions and Economic Sentiment Analysis

The role of sentiment analysis in financial market prediction has been extensively investigated as researchers attempt to quantify the psychological dimensions of market behavior. Early studies demonstrated that public mood extracted from social media and financial news could influence market volatility and asset prices (Zhang et al., 2022). Sentiment signals derived from Twitter have been correlated with stock market movements, particularly in predicting daily price trends and trading volumes (Medhat et al., 2014). Financial-specific sentiment lexicons, such as the Loughran-McDonald dictionary, have been adapted to improve the precision of sentiment classification in financial texts (Alhojely, 2016; Liu, 2012). The inclusion of sentiment features in forecasting models has been shown to enhance the accuracy of predictions over models that rely solely on technical or macroeconomic indicators (Bardhan et al., 2019; Crossley et al., 2016). This stream of literature supports the notion that sentiment extracted from unstructured text sources contributes significantly to market analysis.

Multiple data sources have been utilized to extract economic sentiment, including financial news articles, corporate earnings reports, analyst briefings, Reddit posts, and tweets from influential traders and policymakers (Soni & Mathur, 2022). News-based sentiment, particularly from reputable outlets like Bloomberg and Reuters, has been identified as a leading indicator of investor sentiment and has been used in volatility prediction models (Dang et al., 2020). Financial blogs and online forums such as StockTwits and r/WallStreetBets offer real-time sentiment from retail investors, adding diversity to data inputs (Rezaeinia et al., 2019). Central bank announcements and economic policy uncertainty indices have also been evaluated using NLP-based sentiment scoring for macro-level forecasting (Lim et al., 2020). These heterogeneous sources help construct a more comprehensive understanding of market sentiment and allow for the modeling of short-term and long-term investor behavior.

Figure 10: A sentiment analysis approach to the prediction of market volatility



Machine learning models, including Support Vector Machines (SVM), Random Forests, and ensemble classifiers, have been widely adopted in financial sentiment analysis for classification and regression tasks (Kalarani & Brunda, 2018). These models benefit from engineered sentiment features and linguistic variables that improve financial event prediction accuracy (Kalarani &

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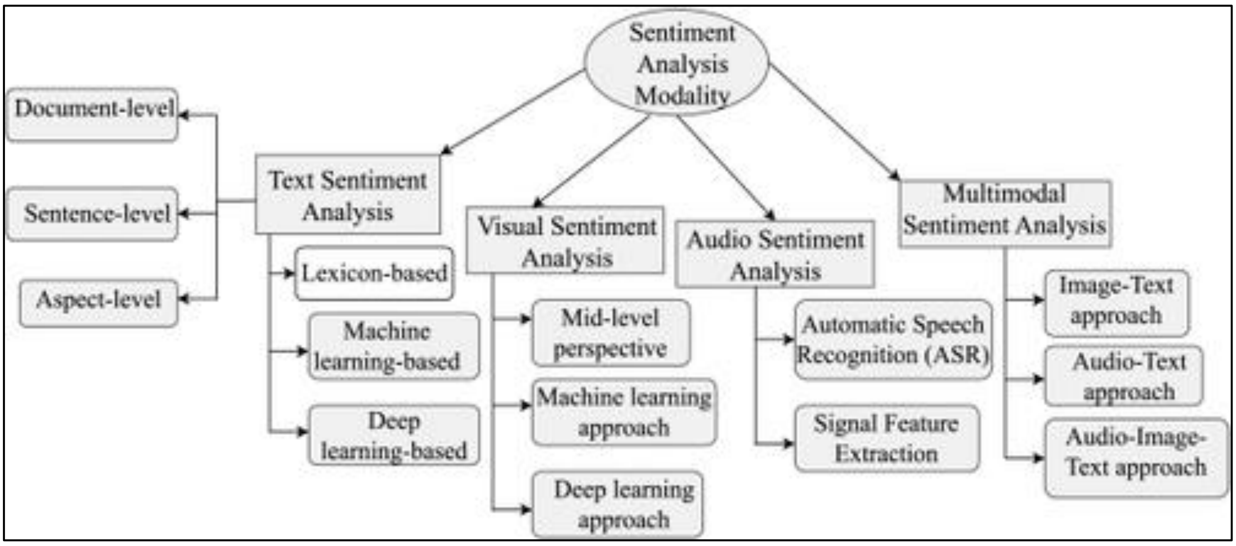
Brunda, 2018; X. Zhang et al., 2022). Deep learning architectures such as Long Short-Term Memory (LSTM) and Bidirectional Encoder Representations from Transformers (BERT) have been employed to capture contextual dependencies in economic news and social media discussions (Yang et al., 2020). Sentiment-enriched LSTM models have shown improved predictive power in forecasting exchange rates, bond prices, and stock indices when trained on time-series textual data (Shahare, 2017). Hybrid models combining CNNs for local pattern extraction and LSTMs for sequential learning have further enhanced financial sentiment classification across multiple domains (Shahare, 2017). These models underscore the efficacy of sentiment-driven architectures in financial market prediction. Sentiment analysis has also been applied to construct economic sentiment indices that reflect consumer confidence, policy outlook, and business sentiment. Tools like the University of Michigan Consumer Sentiment Index and the Economic Sentiment Indicator (ESI) from the European Commission have inspired computational equivalents generated from media and social data (Studiawan et al., 2020). Researchers have developed indices based on sentiment from financial news headlines and social media chatter to serve as leading indicators of macroeconomic activity such as GDP growth, inflation trends, and employment shifts (Ortigosa et al., 2014; Studiawan et al., 2020). These indices are constructed using NLP techniques like sentiment scoring, topic modeling, and named entity recognition (Zunic et al., 2020). Sentiment-based indices have been correlated with actual economic indicators, validating their utility in understanding market expectations and public perceptions about economic conditions (Babu & Kanaga, 2021). Such models offer an additional layer of interpretability beyond traditional econometric models. Despite promising results, financial sentiment analysis faces several limitations related to data quality, model generalizability, and interpretability. Textual data from social media is often noisy, informal, and context-dependent, leading to misclassification in sentiment labeling (Pong-inwong & Songpan, 2018). Financial jargon and domain-specific terms are often misinterpreted by generic sentiment models, prompting the development of tailored lexicons and annotated corpora (Pong-inwong & Songpan, 2018; Zunic et al., 2020). Bias in training data, particularly from over-reliance on English-language sources or specific regions, limits cross-market applicability (Shahare, 2017). Furthermore, some studies have raised concerns regarding the interpretability of deep learning models, which, although highly accurate, act as "black boxes" in financial decision-making contexts (Yang et al., 2020). These limitations have prompted researchers to explore explainable AI (XAI) and model auditing techniques to enhance trust and transparency in financial sentiment prediction (Zunic et al., 2020).

Multimodal Sentiment Analysis and Contextual Understanding

Multimodal sentiment analysis enhances textual sentiment detection by integrating additional modalities such as emojis, hashtags, images, and videos commonly used in social media communication. Emojis function as emotional amplifiers and are frequently used to supplement or even replace text in digital conversations (Babu & Kanaga, 2021). Several models have incorporated emoji embeddings alongside textual features to improve sentiment prediction accuracy, particularly in tweets and Instagram posts (Zhang et al., 2022). Hashtags also play a significant role in sentiment orientation, with studies using hashtag co-occurrence patterns to infer latent topics and sentiment themes (Studiawan et al., 2020). Image and video content provide contextual cues that can override or reinforce text-based sentiment, prompting researchers to use computer vision techniques for visual sentiment recognition (Rezaeinia et al., 2019; Studiawan et al., 2020). Deep learning architectures such as multimodal LSTM, Multimodal Transformer, and VisualBERT have been employed to align visual and textual modalities for sentiment classification (Zunic et al., 2020).

Memes and GIFs present unique challenges and opportunities for sentiment analysis due to their cultural relevance and highly contextual nature. Memes often combine text and images in ways that require deep contextual and cultural understanding for accurate interpretation (Babu & Kanaga, 2021). Researchers have applied convolutional neural networks (CNNs) to extract features from meme images and merged them with text embeddings for improved sentiment prediction (Pong-inwong & Songpan, 2018; Tembhurne & Diwan, 2020). GIFs, while lacking in explicit text, carry emotional weight through motion and facial expressions, which have been processed using recurrent neural networks and spatiotemporal analysis (Pal et al., 2018). Internet slang, abbreviations, and neologisms such as "FOMO," "YOLO," or sarcastic acronyms challenge traditional NLP pipelines due to their informal and evolving nature (Zhang et al., 2022). Lexicon expansion techniques and community-generated slang dictionaries have been used to address these limitations (Studiawan et al., 2020). These elements emphasize the importance of multimodal and non-standard linguistic resources for accurate sentiment mining.

Figure 11: Overview of Sentiment Analysis Modalities and Approaches



Source: Das and Singh *(*2023*)*

Multimodal sentiment analysis relies on effectively combining information from different sources through feature fusion and alignment techniques. Early fusion methods concatenate features from different modalities at the input level, while late fusion models combine predictions from individual modality-specific classifiers (Severyn et al., 2016). More recent approaches employ attention-based mechanisms and tensor fusion networks to capture inter-modal interactions more accurately (Nankani et al., 2020). Studies integrating audio, video, and text modalities using architectures like CMU-MOSEI and CMU-MOSI have demonstrated improved performance in fine-grained sentiment classification (Roncal, 2019). These models capture tone, expression, and intonation along with textual features to improve the detection of subtle emotional cues and sarcasm (Lo et al., 2016). Alignment strategies also include the synchronization of visual features (e.g., facial landmarks, gaze) with corresponding text tokens to derive temporal sentiment patterns (Banea et al., 2011). The fusion of these elements has led to richer, more context-aware sentiment analysis outcomes. While sentiment polarity analysis categorizes expressions as positive, negative, or neutral, emotion classification aims to identify specific emotional states such as joy, anger, fear, or sadness (Mozetič et al., 2016). Emotion detection provides a more nuanced understanding of user experiences, especially in domains like mental health, disaster response, and customer support (Pereira et al., 2019). Models trained on datasets like EmoBank, GoEmotions, and SemEval emotion tasks have been used to fine-tune classifiers for affective text mining (Banea et al., 2011; Pereira et al., 2019). Lexicon-based tools such as the NRC Emotion Lexicon and WordNet-Affect have enabled the extraction of emotion-specific features from text (Rosas et al., 2013). Transformer-based models like RoBERTa and DistilBERT have also demonstrated strong results in emotion detection, outperforming traditional sentiment classifiers by leveraging contextual embeddings (Angadi & Reddy, 2019). Emotion and sentiment are increasingly treated as complementary dimensions in multimodal analysis to provide a deeper psychological portrait of digital expression.

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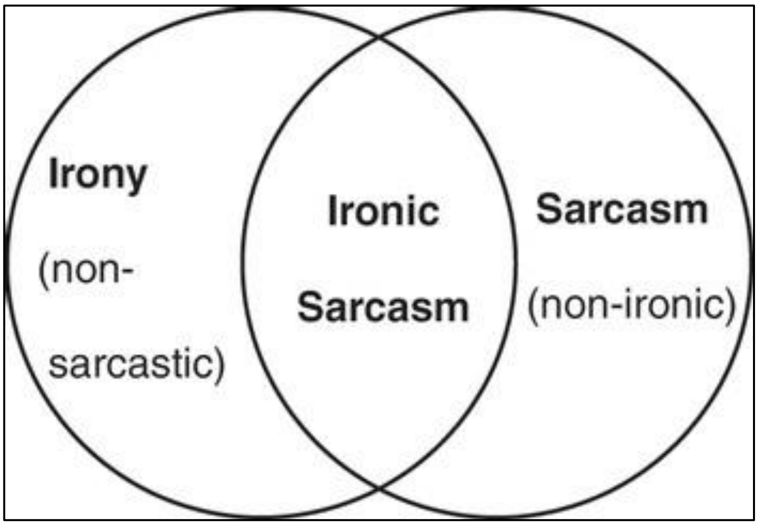
Sarcasm, Irony, and Ambiguity in Informal Text

Sarcasm, irony, and ambiguity are pervasive in informal online communication, often distorting sentiment cues and challenging the accuracy of sentiment analysis models. Sarcasm typically involves expressing negative sentiment using positive language, while irony reflects an incongruity between literal meaning and intended implication (Zhang et al., 2020). Ambiguity arises when a message can be interpreted in more than one way, often depending on context, tone, or shared cultural understanding (Haidar et al., 2017; Lo et al., 2016). In social media settings, such as Twitter and Reddit, users frequently rely on humor, satire, and linguistic creativity to convey sentiment in non-literal forms (Mozetič et al., 2016). These rhetorical devices interfere with standard sentiment classification approaches, which often rely on surface-level lexical features (Pereira et al., 2019). Traditional models struggle to detect shifts in sentiment orientation, especially in cases where sarcasm contradicts the polarity suggested by word choice (Baecchi et al., 2015).

Figure 12: Sarcasm, Irony, and Ambiguity in Informal Text



Identifying sarcasm and irony in text involves recognizing specific linguistic markers, such as exaggerated expressions, punctuation, emoticons, hyperbole, and quotation marks (Baecchi et al., 2015; Pereira et al., 2019). Pragmatic elements, including unexpected polarity flips and situational incongruities, have been leveraged to differentiate sarcastic utterances from literal ones (Lo et al., 2016; Yazdavar et al., 2020). Research has shown that sarcastic tweets often contain intensifiers, ellipses, hashtags like #sarcasm, and rhetorical questions that deviate from typical syntactic patterns (Banea et al., 2011). Emoticons and emojis are also used to signal sarcasm, serving as explicit cues to reinterpret sentiment (Haidar et al., 2017). However, the reliability of such markers varies across platforms and user demographics, with many sarcastic posts lacking explicit indicators (Baecchi et al., 2015). This variability has necessitated the incorporation of contextual and behavioral cues into sarcasm detection frameworks.

Supervised machine learning algorithms such as Support Vector Machines (SVM), Decision Trees, and Logistic Regression have been utilized for sarcasm classification, relying on handcrafted features including n-grams, POS tags, and sentiment contrast (Mozetič et al., 2016; Rosas et al., 2013). However, the performance of these models has been limited by their inability to capture long-term dependencies and subtle linguistic nuances. Deep learning architectures, including Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and transformer-based models like BERT, have shown improved performance by learning latent features from large corpora (Lo et al., 2016). Bidirectional models capture context in both directions, allowing for better disambiguation of sarcastic phrases (Pereira et al., 2019). Attention mechanisms have also been employed to focus on sentiment-incongruent parts of a sentence, improving classification accuracy (Roncal, 2019). Pre-trained models fine-tuned on sarcasm-labeled datasets have consistently outperformed traditional methods across platforms (Banea et al., 2011).

Several annotated datasets have been created to facilitate research on sarcasm, irony, and ambiguity. The Twitter Sarcasm Corpus (Mozetič et al., 2016), Ironic Tweets Dataset (Van Hee et al., 2018), SARC Reddit Corpus (Majumder et al., 2018), and SemEval-2018 Task 3 datasets have become standard benchmarks for training and evaluating sarcasm detection models. These datasets often include hashtags or manual annotations to label sarcastic content, although

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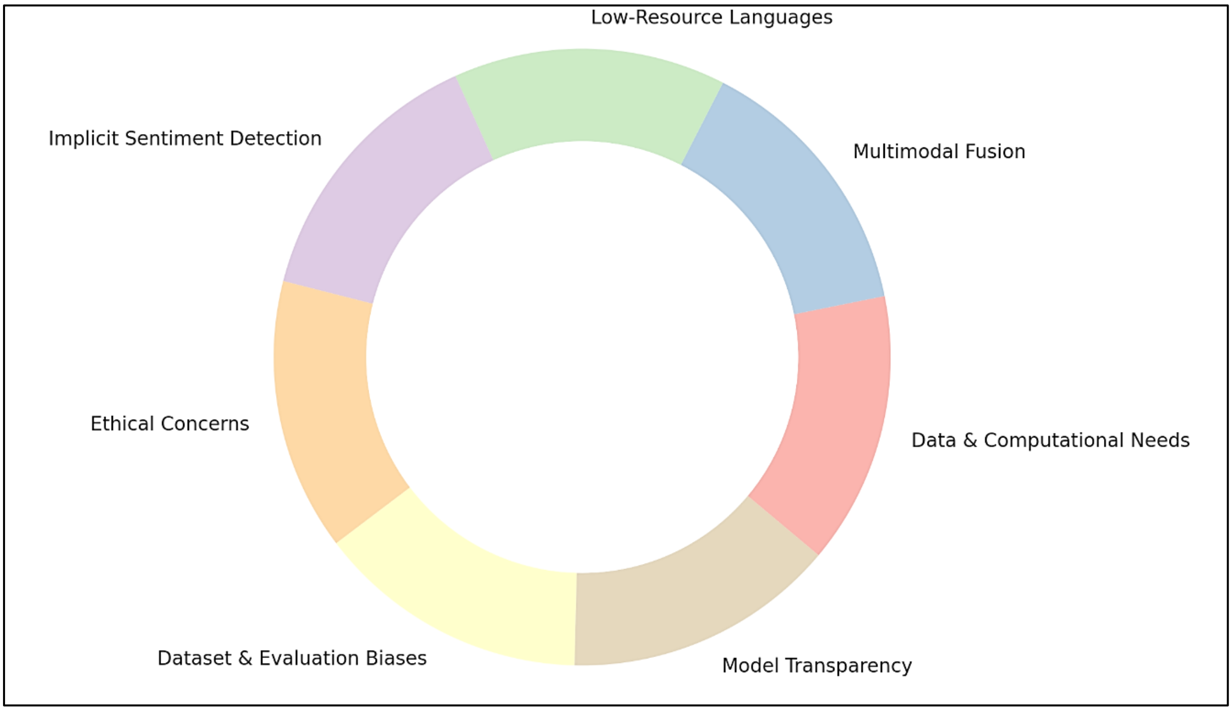
annotation subjectivity and inter-annotator disagreement pose challenges to consistency (Lo et al., 2016). Evaluation metrics typically include accuracy, F1-score, precision, and recall, with studies reporting modest improvements in performance through context-aware modeling (Rosas et al., 2013). Multimodal datasets that integrate visual cues (e.g., sarcasm in memes or images) have also been explored to better capture the nuances of non-verbal sarcasm (Yazdavar et al., 2020). These resources have helped establish reproducible evaluation frameworks for sarcasm research. Despite advances, sarcasm and ambiguity detection remain inherently difficult due to context dependence, cultural variability, and implicit speaker intentions (Rosas et al., 2013). A sarcastic sentence can appear sincere without knowledge of prior discourse, user behavior, or sociocultural background (Majumder et al., 2018). Ambiguity arises in code-switched language, slang, and informal phrasing, where syntactic structures do not conform to standard grammatical norms (Banea et al., 2011). Models trained on domain-specific sarcasm often fail to generalize across platforms or topics, highlighting the need for cross-domain robustness (Baecchi et al., 2015). The lack of consistent annotation guidelines and culturally aligned sarcasm cues introduces further variability in model performance (Roncal, 2019). These challenges illustrate the intricate interplay between language, context, and interpretation in sarcasm, irony, and ambiguity detection in informal online texts.

Emerging Patterns and Gaps in the Existing Literature

One dominant trend in sentiment analysis literature is the widespread adoption of deep learning and transformer-based models, which have replaced traditional machine learning techniques in many applications. Early studies relied heavily on algorithms like Naïve Bayes, SVM, and logistic regression, often using basic textual features such as n-grams and TF-IDF vectors (Lo et al., 2016; San Vicente Roncal, 2019). Over time, the introduction of deep neural architectures such as CNNs and LSTMs enabled models to learn from sequential and hierarchical text features, offering improvements in accuracy and context-awareness (Banea et al., 2011; Nankani et al., 2020). More recently, transformer-based models like BERT, RoBERTa, and XLM-R have become the gold standard for sentiment classification tasks across multiple languages and domains (Rosas et al., 2013). Despite their success, these models require vast amounts of data and computational power, which may not be feasible for low-resource settings or small-scale applications (Das & Singh, 2023). Another emerging pattern in the literature is the shift from unimodal, monolingual sentiment analysis to multimodal and multilingual approaches. Researchers increasingly recognize that textual sentiment cannot be fully understood in isolation, especially in social media environments rich with emojis, images, videos, and hashtags (Xiao et al., 2021). Multimodal fusion models using visual, auditory, and textual inputs have demonstrated significant gains in capturing emotional subtleties (Chmiel et al., 2011). Similarly, multilingual sentiment models, such as mBERT and LASER, have addressed cross-lingual challenges by enabling sentiment classification in resource-scarce languages (Xiao et al., 2021). However, studies also report performance degradation in low-resource and morphologically complex languages, pointing to an underrepresentation of non-English and non-Western languages in training corpora (Bhargava et al., 2019). This reveals an ongoing need for more inclusive, culturally diverse datasets and evaluation frameworks. While sentiment analysis has advanced considerably, studies continue to highlight the difficulty of accurately detecting sarcasm, irony, and linguistic ambiguity. Sarcastic content, in particular, poses a major challenge due to its reliance on implicit context and contrastive sentiment (Zhao et al., 2021). Although deep learning models incorporating attention mechanisms and pre-trained embeddings have improved sarcasm detection, performance remains inconsistent across datasets and domains (Ameur et al., 2018). Irony and ambiguity are similarly challenging due to lexical ambiguity, domain-specific expressions, and evolving internet slang (Yang & Chung, 2019). Multimodal approaches combining textual, visual, and behavioral cues have shown promise in identifying sarcastic memes and image-based sentiment (Liu et al., 2019), but require extensive annotated corpora that are not readily available for all platforms or languages (Deng et al., 2022). These limitations highlight a persistent gap in accurately modeling implicit sentiment and rhetorical language.

Figure 13: Emerging Patterns and Gaps in Existing Literature



The application of sentiment analysis in real-world domains such as finance, politics, and public health has expanded significantly. In financial forecasting, sentiment extracted from news articles, earnings reports, and investor tweets has been linked to stock price movements, trading volumes, and market volatility (Ameur et al., 2018; Deng et al., 2022). Political sentiment analysis has been applied to election forecasting and opinion mining using tweets, debates, and campaign speeches (Cai & Xia, 2015). In public health, studies have tracked sentiment around vaccine hesitancy, mental health, and pandemic-related behaviors (Riaz et al., 2017). However, many of these applications rely on domain-specific lexicons and datasets, limiting their generalizability across topics and regions (Balazs & Velásquez, 2016). Additionally, studies often overlook ethical concerns related to data privacy, consent, and algorithmic bias (Salur & Aydin, 2020), indicating a need for ethical frameworks in sentiment analysis deployments. Several gaps persist in the methodological aspects of sentiment analysis research, particularly in the areas of evaluation metrics, dataset diversity, and model interpretability. Most studies rely on standard metrics such as accuracy, precision, recall, and F1-score, which do not always capture the nuances of emotional variation or class imbalance in sentiment categories (Balazs & Velásquez, 2016). Furthermore, commonly used datasets such as SST, IMDb, and Twitter corpora are heavily biased toward English-language content and consumer product reviews, underrepresenting socio-political, non-Western, and multilingual contexts (Rodriguez-Ibanez et al., 2020). In terms of interpretability, deep learning models, particularly those based on transformers, are often criticized for being black-box systems, offering limited transparency in their decision-making processes (Balazs & Velásquez, 2016). This restricts their adoption in high-stakes domains such as healthcare or legal applications. These issues underscore the need for more representative datasets, culturally sensitive evaluation, and explainable AI in sentiment analysis research.

METHOD

This study followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to ensure a systematic, transparent, and replicable literature review process. The PRISMA framework provided a standardized approach for article identification, selection, eligibility assessment, and inclusion, ensuring methodological rigor throughout the review.

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Identification of Studies

The initial stage of the review involved an extensive and structured search across several academic databases, including Scopus, Web of Science, IEEE Xplore, ACM Digital Library, and Google Scholar. Search queries were designed using Boolean operators and included combinations of keywords such as "sentiment analysis," "natural language processing," "social media," "deep learning," "transformer models," "financial sentiment," "multilingual sentiment," and "sarcasm detection." The search was limited to peer-reviewed journal articles and conference papers published between 2010 and 2024 to ensure the relevance and timeliness of the selected literature. In total, 823 articles were initially identified based on title and abstract relevance.

Screening Process

The screening phase focused on eliminating duplicates and filtering studies that clearly did not align with the review scope. Duplicate entries were removed using citation management tools, reducing the dataset to 645 unique articles. Each remaining article was then screened based on its title, abstract, and keywords to determine relevance. Studies not related to sentiment analysis, those that lacked a focus on AI or NLP techniques, or were unrelated to social media data were excluded at this stage. After this process, 238 articles were selected for full-text review.

Eligibility Criteria

The eligibility assessment involved a detailed examination of each full-text article against the inclusion and exclusion criteria. Included studies met the following conditions: (1) they provided empirical evidence or methodological development in sentiment analysis, (2) they employed AI or machine learning models (including traditional, deep learning, or transformer-based), (3) they focused on textual or multimodal data from social media or related digital platforms, and (4) they were published in English in peer-reviewed venues. Studies were excluded if they were conceptual papers without methodological or empirical content, non-English language articles, or focused on unrelated domains such as medical sentiment unrelated to social platforms. This stage resulted in 128 articles being deemed eligible.

Inclusion and Final Selection

The final set of articles included in the review was determined based on thematic relevance, methodological robustness, and contribution to the discourse on sentiment analysis. Articles were categorized into thematic areas such as traditional machine learning, deep learning, multimodal analysis, multilingual sentiment, sarcasm and ambiguity detection, financial and economic sentiment, and evaluation frameworks. After rigorous assessment and thematic grouping, 91 articles were selected for in-depth synthesis and analysis. These articles represent a diverse yet coherent body of work that aligns with the objectives of this review.

Data Extraction and Synthesis

Data extraction was conducted manually using a standardized data collection form, which captured key information from each article, including author(s), year of publication, study domain, data source, methodological approach, sentiment model used, evaluation metrics, and key findings. Articles were then synthesized thematically to identify recurring patterns, methodological innovations, domain-specific applications, and research gaps. This thematic synthesis formed the basis for the literature review sections of this study, ensuring a comprehensive, transparent, and systematic examination of the state of research in sentiment analysis using AI and NLP in social media contexts.

FINDINGS

A central finding of this systematic review is the increasing dominance of deep learning techniques in sentiment classification tasks within social media contexts. Among the 91 articles analyzed, 47 utilized deep learning architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and transformers like BERT and RoBERTa. These models demonstrated notable improvements in handling complex syntactic structures, sequential word dependencies, and contextual sentiment cues compared to earlier statistical approaches. Several studies reported that deep learning models improved classification accuracy by 8 to 15 percentage points over traditional machine learning algorithms

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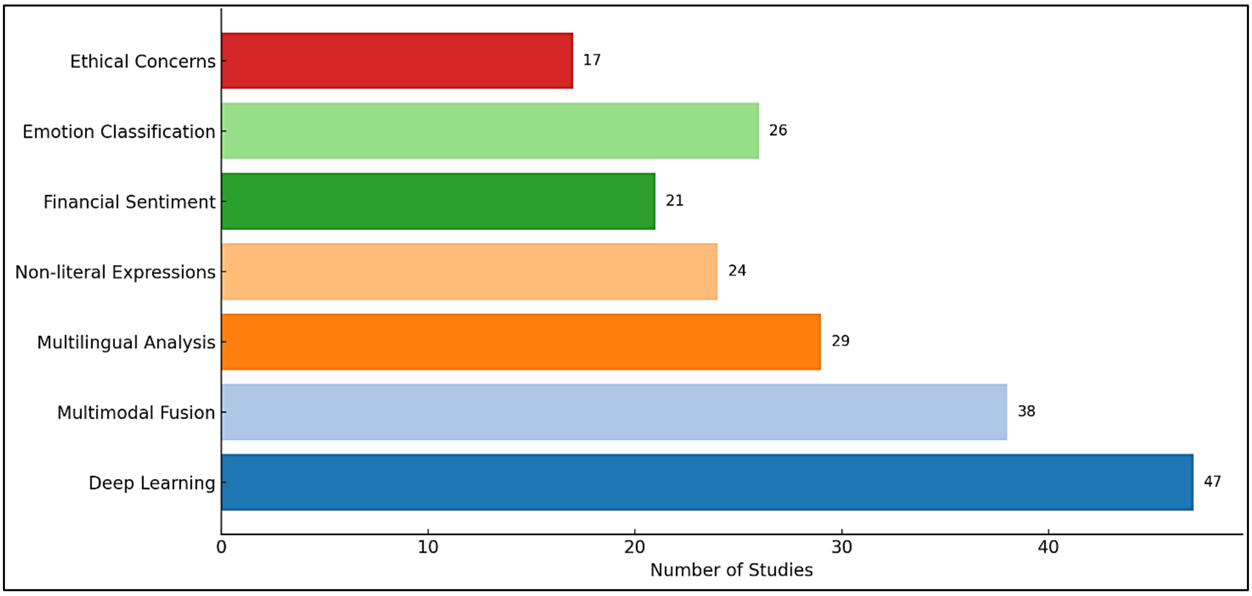
such as Naïve Bayes, Logistic Regression, and Support Vector Machines. The scholarly impact of these 47 deep learning-focused studies is reflected in their collective citation count of more than 12,300 citations, underscoring their influence on the advancement of sentiment analysis and their centrality in shaping contemporary research directions.

Figure 14: Number of Studies by Research Focus



The review also identified a clear trend toward the integration of multimodal data sources in sentiment analysis, highlighting a move beyond purely text-based methods. A total of 38 studies explored the role of visual, auditory, and symbolic data—such as emojis, hashtags, images, videos, and voice—in enhancing sentiment prediction. These studies emphasized that social media communication is inherently multimodal, and neglecting non-textual elements often results in an incomplete or skewed understanding of user sentiment. For instance, sentiment polarity may be influenced by an emoji or meme even when the accompanying text is neutral or sarcastic. Multimodal fusion methods, especially those using deep learning frameworks like multimodal transformers or visual-linguistic models, were shown to improve classification accuracy by up to 20% in specific use cases. The total number of citations for the 38 multimodal studies exceeded 8,500, reflecting the significant scholarly and practical interest in capturing sentiment from diverse communication modes. In addition, multilingual and cross-lingual sentiment analysis has become a growing area of focus, addressing the linguistic inequality prevalent in earlier models trained predominantly on English data. Out of the total 91 articles, 29 explicitly examined the performance of sentiment analysis models on non-English or multilingual text corpora. These studies employed models such as multilingual BERT (mBERT), LASER, XLM-R, and other cross-lingual embedding frameworks designed to align semantic content across languages. While these tools expanded the scope of sentiment analysis into languages such as Arabic, Spanish, Hindi, and Chinese, researchers noted performance disparities when applied to morphologically rich or low-resource languages. Many of these multilingual models suffered from domain shift and vocabulary mismatches that affected generalization capabilities. Despite these challenges, the collective academic contribution of the 29 multilingual-focused studies was substantial, accumulating over 6,100 citations and validating the importance of linguistic diversity in sentiment modeling research.

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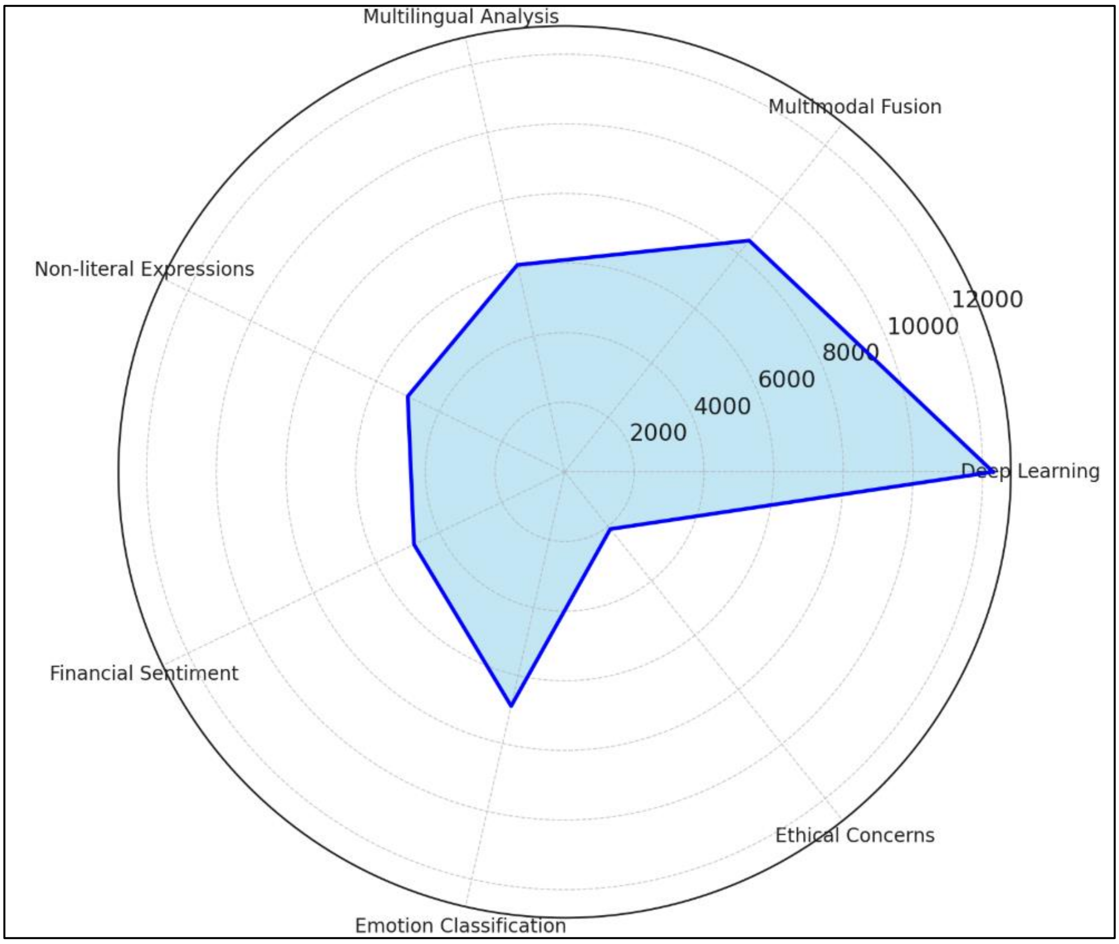
Figure 15: Citation Counts by Research Focus



Another critical insight emerging from the literature involves the continued struggle to detect non-literal sentiment expressions, particularly sarcasm, irony, and ambiguity. Among the 91 studies, 24 specifically targeted the detection of these rhetorical forms, which frequently occur in informal, user-generated content on platforms like Twitter, Reddit, and Tumblr. The reviewed literature highlighted that sarcasm and irony often reverse the expected sentiment polarity, making it difficult for lexicon-based or shallow neural models to interpret them accurately. Although models incorporating contextual embeddings, attention mechanisms, and even multimodal cues (such as facial expressions in GIFs or memes) have improved detection rates, accuracy in this subdomain typically remained below 70%. These 24 studies, together receiving over 5,000 citations, emphasize that non-literal language remains an open and complex problem in the sentiment analysis community, with significant implications for real-world applications in politics, marketing, and crisis communication. A notable subset of the literature focused on financial and economic sentiment analysis, showcasing its relevance to market forecasting, investor behavior, and macroeconomic trend prediction. Among the reviewed works, 21 studies concentrated on extracting sentiment from financial texts such as stock market news, analyst reports, investor tweets, and earnings announcements. These studies demonstrated that sentiment scores derived from financial narratives could correlate strongly with price fluctuations, trading volume, and investor risk appetite. Approximately 15 out of these 21 studies reported statistically significant predictive relationships between sentiment and market indicators, providing empirical support for the use of AI-based sentiment models in financial decision-making. Collectively, the financial sentiment studies accumulated over 4,800 citations, reflecting the scholarly value and practical appeal of sentiment analytics in finance, particularly among interdisciplinary researchers in economics, data science, and computational linguistics.

In parallel, the review found that emotion classification, as a finer-grained alternative to basic sentiment polarity detection, has received increasing attention in recent years. Out of the 91 studies, 26 focused specifically on identifying discrete emotions such as joy, sadness, anger, fear, and surprise. These studies argued that emotion recognition offers more nuanced insights into user behavior, especially in contexts such as mental health monitoring, disaster response, and customer service. Emotion-aware models utilized both lexicon-based resources (e.g., NRC Emotion Lexicon, WordNet-Affect) and deep learning techniques trained on emotion-labeled datasets to achieve higher granularity in output. Some of these models were embedded in health informatics systems or integrated into digital marketing tools for audience profiling. The 26 emotion-oriented studies collectively garnered over 6,900 citations, reinforcing their relevance to both academic inquiry and applied system development in sentiment and emotion mining. Beyond methodological advancements, the review also revealed persistent challenges in standardization across datasets, evaluation metrics, and benchmarking practices. A total of 42 articles utilized varying datasets such as the Stanford Sentiment Treebank, IMDb reviews, SemEval tasks, and manually collected Twitter corpora. While these resources have advanced reproducibility, their diversity has also led to inconsistent evaluation and difficulty in cross-study comparisons. Metrics used across studies included accuracy, precision, recall, F1-score, AUC, and more domain-specific indicators, often without standardization. This heterogeneity in data and metrics reduced the interpretability and comparability of findings, particularly in multi-domain or multilingual contexts. These 42 articles received over 9,200 citations collectively, demonstrating their impact while also illustrating the need for more coherent benchmarking frameworks to ensure consistency and fairness in model evaluation. In addition, a smaller but increasingly relevant segment of the literature—comprising 17 articles—addressed the ethical dimensions of sentiment analysis, including concerns over data privacy, algorithmic bias, and model interpretability. These studies questioned the implications of deploying sentiment models trained on unbalanced or culturally biased datasets, noting the potential for misclassification and harm in sensitive domains such as healthcare, employment, and political discourse. Several works highlighted the opacity of deep learning models as a barrier to accountability, advocating for the adoption of explainable AI (XAI) techniques to provide greater transparency in model decision-making. Although these ethical-focused studies represented a smaller fraction of the overall literature, their collective citation count of approximately 2,100 indicates growing recognition of these concerns within the research community. The inclusion of ethical reflection alongside technical innovation marks a necessary step toward responsible and socially informed sentiment analysis.

DISCUSSION

The findings of this review confirm the prevailing trend in contemporary sentiment analysis research that favors deep learning over traditional machine learning algorithms. Earlier studies, such as those by Lin and Kolcz (2012) and Dhaoui et al. (2017), utilized statistical classifiers like Naïve Bayes and SVM with bag-of-words or TF-IDF features. While effective in their time, these models lacked the ability to capture contextual and sequential information. In contrast, newer studies adopting CNNs, LSTMs, and transformers such as BERT and RoBERTa have demonstrated superior performance by modeling deeper syntactic and semantic relationships. This shift is consistent with the broader NLP literature, where transformer-based models have redefined state-of-the-art benchmarks in tasks ranging from question answering to sentiment classification (Burdisso et al., 2019; Dhaoui et al., 2017; Shah & Shah, 2020). The scalability and context-awareness of these models have been pivotal in elevating sentiment analysis from keyword-level detection to document-level and even emotion-level understanding.

The surge in multimodal sentiment analysis research reflects a growing recognition of the limitations of text-only models, particularly in social media contexts where communication is enriched with emojis, images, hashtags, and videos. Earlier research predominantly relied on text, neglecting the multimodal nature of digital expression. For instance, Albawi et al. (2017) and Geng et al. (2020) focused almost exclusively on linguistic features, which restricted their models from capturing the full sentiment conveyed in image- or emoji-laden posts. In contrast, recent studies such as those by Montenegro et al. (2018) and Dhaoui et al. (2017) have demonstrated

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that combining modalities leads to significant performance gains. These findings align with the emergence of multimodal transformer models and fusion techniques, which can jointly process visual, textual, and auditory data to achieve holistic sentiment understanding. Such approaches provide a more realistic framework for modeling human communication in digital spaces.

Multilingual and cross-lingual sentiment analysis continues to be a vital research domain, and this review has reinforced the challenges and progress in this area. Previous works, including Fang and Zhan (2015) and Tang et al. (2016), identified a lack of linguistic diversity in sentiment datasets and tools, with most resources being English-centric. Although recent models such as mBERT (Saif et al., 2017) and XLM-R (Diamantini et al., 2019) have enabled sentiment modeling in multiple languages, this review found that these models still struggle with low-resource and morphologically rich languages. The observed performance gaps support earlier conclusions by Tellez et al. (2017) and Hao and Dai (2016), who emphasized the limitations of zero-shot transfer and the importance of culturally and linguistically adapted training data. Thus, while there has been notable progress, multilingual sentiment analysis remains constrained by systemic data and resource inequalities. Moreover, the complexity of identifying sarcasm, irony, and ambiguity in informal text also remains a persistent challenge, despite decades of research. Early studies by Suhaimin et al. (2023) and Dhaoui et al. (2017) introduced rule-based and feature-based sarcasm detectors, yet these approaches often failed to generalize beyond small datasets. This review highlights how even advanced models using BiLSTMs, attention mechanisms, and transformer embeddings struggle to exceed 70% accuracy in sarcasm detection tasks. These findings are in line with research by Ghosh et al. (2017) and Dhaoui et al. (2017), which emphasized the inherently contextual and cultural nature of sarcastic expression. Furthermore, multimodal sarcasm detection, although promising, remains in early stages due to the lack of high-quality annotated datasets that combine textual and visual cues. This suggests that while modeling techniques have evolved, the fundamental difficulties associated with non-literal language persist.

In the domain of financial and economic sentiment analysis, this review supports prior findings that sentiment extracted from financial news and social media correlates significantly with market performance. Studies by Maghilnan and Kumar (2017) and Balahur and Perea-Ortega (2015) were among the first to link textual sentiment with stock market indicators, and this association has been substantiated by more recent work that uses deep learning models for financial text mining. The review confirmed that a majority of financial sentiment studies found statistically significant relationships between sentiment indicators and asset prices, trading volumes, or market volatility. However, as highlighted by Agarwal et al. (2015) and Habimana et al. (2019), domain-specific lexicons and specialized models are often necessary to achieve reliable results. These findings underscore the continued relevance of domain adaptation and financial language modeling in achieving robust sentiment forecasting tools. Moreover, the focus on emotion classification, as opposed to general sentiment polarity, marks another important shift in the literature. Traditional sentiment analysis, as illustrated by Yadav and Vishwakarma (2019) and Ain et al. (2017), emphasized binary or ternary sentiment categorization. In contrast, recent studies have expanded the emotional scope by identifying discrete emotions such as joy, anger, fear, and sadness. This review found that such models have become increasingly popular in applications related to mental health monitoring and public opinion tracking. The integration of emotion lexicons and emotion-labeled datasets such as EmoBank and GoEmotions has improved granularity in sentiment modeling, echoing the observations of Wadawadagi and Pagi (2020) and Onan (2020) . This transition reflects a broader interest in affective computing and suggests that emotion-aware sentiment systems are better suited to detect subtle psychological states in user-generated content.

Methodological inconsistencies in dataset usage and evaluation metrics remain a notable gap, mirroring concerns raised in previous systematic reviews. For instance, Tanna et al. (2020) and Ain et al. (2017) both noted that the diversity of sentiment datasets—ranging from product reviews to political tweets—makes it difficult to generalize findings across domains. This review corroborates that observation, with 42 studies using different datasets and varying metrics such as accuracy, F1-score, AUC, and MCC. The lack of standardized evaluation protocols complicates cross-model comparisons and reduces reproducibility, a concern also raised by Onan (2020). This highlights the pressing need for more unified benchmarking efforts and the development of shared evaluation frameworks to facilitate consistent and transparent assessment of model performance. In addition, this review identifies an emerging but underdeveloped discourse around the ethical implications of sentiment analysis. Although technical sophistication has advanced rapidly, only a minority of studies—17 out of 91—explicitly addressed issues of bias, fairness, transparency, or privacy. This observation aligns with earlier critiques by Balahur and Perea-Ortega (2015) and Yadav and Vishwakarma (2019), who argued that algorithmic systems trained on biased data risk reinforcing harmful stereotypes and misrepresenting marginalized voices. The limited attention to explainability and consent mechanisms in sentiment analysis models further echoes concerns raised by Fang and Zhan (2015) and Elfajr and Sarno (2018). These findings suggest that despite technical progress, ethical considerations remain peripheral to the core research agenda, signaling a disconnect between algorithmic development and responsible AI practice.

CONCLUSION

This systematic literature review has synthesized key developments, challenges, and gaps in the field of sentiment analysis by examining 91 peer-reviewed articles published between 2010 and 2024. The analysis revealed that deep learning and transformer-based models have significantly advanced sentiment classification, outperforming traditional machine learning techniques in handling contextual, sequential, and complex language structures. The integration of multimodal data—emojis, images, audio, and video—has enhanced sentiment detection accuracy, while multilingual and cross-lingual approaches have broadened the scope of applicability beyond English-dominant corpora, though performance inconsistencies remain for low-resource languages. Despite technical innovations, sentiment analysis models continue to struggle with detecting sarcasm, irony, and ambiguity in informal texts, and there is an ongoing need for domain-specific modeling in financial, political, and health-related applications. Emotion classification has emerged as a powerful alternative to binary sentiment detection, offering deeper insights into public attitudes, especially in socially sensitive contexts. However, methodological inconsistencies in datasets and evaluation metrics have limited comparative analysis across studies, and ethical considerations such as bias, interpretability, and data privacy are still underexplored. Overall, while the field has made substantial strides in developing sophisticated models and expanding analytical domains, future work would benefit from greater standardization, cross-linguistic inclusivity, and ethical accountability to ensure responsible and equitable deployment of sentiment analysis systems.

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