Sentiment Analysis on Web and Social Media Texts: A Comparative Study of Methods and Limitations

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Abstract
Sentiment analysis has emerged as a crucial research area for understanding opinions expressed in web and social media texts, driven by the exponential growth of user-generated content on platforms such as social networks, microblogs, forums, and e-commerce websites. These texts provide valuable insights into public perception, consumer behavior, and societal trends. However, analyzing such data is challenging due to informal language, domain dependency, multilingual diversity, ambiguity, and implicit sentiment expressions. This paper presents a comparative study of sentiment analysis methods applied to web and social media texts, focusing on lexicon-based approaches, traditional machine learning models, and advanced deep learning techniques. By systematically reviewing existing studies, we analyze the methodologies, datasets, performance outcomes, advantages, and limitations of each approach. The study highlights that while lexicon-based methods offer interpretability and efficiency, they suffer from limited coverage, whereas machine learning and deep learning models provide higher accuracy at the cost of data dependency and computational complexity. Comparative analysis reveals persistent research gaps related to dataset scarcity, cross-domain generalization, and standardized evaluation practices. This study aims to assist researchers in selecting appropriate sentiment analysis techniques and to identify promising directions for future research.

Keywords: Sentiment Analysis, Opinion Mining, Web Text, Social Media Analysis, Machine Learning, Deep Learning

1. Introduction

The rapid advancement of web technologies and the widespread adoption of social media platforms have transformed the way individuals express opinions, emotions, and attitudes. Users now actively share feedback through online reviews, tweets, comments, blogs, and discussion forums, generating an unprecedented volume of unstructured textual data. This surge of opinion-rich content has created significant opportunities for businesses, policymakers, and researchers to extract actionable insights related to customer satisfaction, brand reputation, market trends, and public sentiment. Consequently, sentiment analysis, also referred to as opinion mining, has become a vital subfield of natural language processing (NLP) and text mining [1].

Sentiment analysis focuses on identifying and classifying subjective information in text, typically into positive, negative, or neutral categories. Early research primarily addressed document-level and sentence-level sentiment classification, which assigns an overall polarity to a piece of text. While effective in many scenarios, such coarse-grained analysis often fails to capture nuanced opinions expressed toward specific entities or aspects within a text. This limitation led to the emergence of aspect-based sentiment analysis (ABSA), which aims to determine sentiment polarity toward aspects or features of a product, service, or topic [2].

Web and social media texts pose unique challenges for sentiment analysis. Unlike traditional textual data, online content is often informal, noisy, and highly dynamic. It frequently includes slang, abbreviations, emojis, sarcasm, misspellings, and domain-specific terminology. Additionally, social media texts are typically short and context-dependent, making it difficult to accurately interpret sentiment. Multilingual diversity further complicates the task, as many languages lack sufficient annotated datasets and linguistic resources [3].

Over the years, various sentiment analysis approaches have been proposed to address these challenges. Lexicon-based methods rely on predefined sentiment dictionaries to compute polarity scores. These methods are simple, interpretable, and computationally efficient, making them suitable for real-time applications. However, their performance is constrained by limited vocabulary coverage, difficulty handling polysemous words, and inability to adapt to evolving language usage. To overcome these limitations, machine learning approaches such as Naïve Bayes, Support Vector Machines, K-Nearest Neighbors, and Logistic Regression have been widely adopted. These methods leverage statistical patterns learned from labeled data and generally outperform lexicon-based techniques in terms of accuracy.

With the rise of deep learning, sentiment analysis has witnessed a paradigm shift. Neural network architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and transformer-based models like BERT have demonstrated remarkable performance improvements. These models can automatically learn complex semantic and contextual representations from large-scale datasets, enabling more accurate sentiment classification. Nevertheless, deep learning models require substantial annotated data, high computational resources, and often lack interpretability [4].

Despite the progress achieved, existing sentiment analysis studies often focus on specific domains, platforms, or languages, limiting their generalizability. Moreover, there is a lack of standardized evaluation frameworks and benchmark datasets, making it difficult to fairly compare different approaches. Many studies also overlook implicit sentiment expressions, sarcasm, and cross-domain adaptation, which remain open challenges [5].

In this context, a comprehensive comparative analysis of sentiment analysis methods applied to web and social media texts is essential. This paper aims to systematically examine existing approaches, highlighting their strengths and limitations, and to identify key research gaps that hinder the development of robust and scalable sentiment analysis systems. By synthesizing insights from diverse studies, this work provides a clear understanding of the current state of sentiment analysis research and offers guidance for future advancements [6].

2. Literature review

Obiedat et al. (2021), Aspect-based sentiment analysis (ABSA) for Arabic has gained interest as comments grow on social media and e-commerce. Yet Arabic ABSA remains difficult due to NLP complexity and the limited availability of annotated corpora. This systematic review covers methods, techniques, and datasets used for Arabic ABSA, analyzing 21 studies published between 2015–2021. Key findings include a shortage of reusable annotated datasets and limited domain coverage in existing datasets. The review is intended to guide researchers toward building stronger models and resources. **[1]**

Xu et al. (2019), Dictionary-based sentiment analysis often suffers from limited word coverage and difficulty handling polysemous words whose polarity changes by domain/context. This paper builds an extended sentiment dictionary that includes basic sentiment terms, domain-specific words, and polysemic words. A Naive Bayes classifier first determines the text's domain, then assigns the appropriate polarity value for polysemic words in that domain. Using the extended dictionary plus sentiment-scoring rules, the method achieves feasible and improved sentiment recognition for comment texts. **[2]**

Liu et al. (2022), Rule-based lexicons and machine-learning vector classification are common in sentiment analysis but both have weaknesses (rigid rules, weak prominence of sentiment cues). This paper proposes a weight-distribution approach that combines the two, producing sentence vectors that emphasize sentiment-bearing words while preserving broader text information. Experiments report sentiment classification accuracy up to 82.1%, outperforming pure lexicon rules and TF-IDF weighting baselines by notable margins. The approach aims to balance interpretability with stronger discriminative features. **[3]**

Wang et al. (2020), Twitter sentiment analysis is hard because tweets are short and ambiguous, and many methods use only text. This work argues that sentiment diffusion patterns (how sentiment spreads) correlate with tweet polarity. It studies "sentiment reversal" in diffusion and then proposes SentiDiff, an iterative algorithm that fuses textual signals with diffusion features to predict sentiment. Reported experiments on real datasets show PR-AUC improvements of about 5.09–8.38% versus state-of-the-art text-only baselines, suggesting network dynamics add useful information. **[4]**

Poria et al. (2023), This article reviews sentiment analysis as a field after nearly two decades of development and broad commercial adoption. While polarity classification and benchmark datasets appear mature, the paper challenges the idea that sentiment analysis is "solved." It identifies shortcomings and under-explored issues required for true sentiment understanding, reflects on the breakthroughs that drove the field's relevance, and proposes future research directions targeting deeper, more comprehensive sentiment modeling beyond simple polarity. **[5]**

Yang et al. (2022), Existing ABSA methods often learn sentiment features by modeling dependencies between aspect terms and context, but may ignore external affective commonsense knowledge that could enhance interaction modeling. This paper proposes AKM-IGCN, a knowledge-aware model that augments interactive GCNs with affective knowledge and uses multi-head self-attention to capture richer syntactic/semantic interactions. It targets Chinese-oriented ABSA while also supporting English, evaluated on four Chinese datasets and six English benchmarks. Reported results show the model matches or outperforms prior state-of-the-art approaches. **[6]**

Li et al. (2020), Danmaku (live on-screen comments) captures viewers' real-time reactions and provides "emotional timing" aligned with video moments, but standard sentiment classifiers don't fit its short, fast, context-heavy text. This paper builds a danmaku sentiment dictionary and proposes sentiment analysis using a dictionary plus Naive Bayes. It extracts emotional signals, classifies sentiment, visualizes results, and derives time distributions across seven sentiment dimensions. A weighting scheme is also used to determine polarity. Experiments show strong impact on sentiment scoring and polarity detection. **[7]**

Phan et al. (2020), Tweet sentiment analysis is important due to massive Twitter content and its use in decision support and recommendation systems. Prior feature-ensemble methods often model syntax but miss sentiment context, word position, and fuzzy-sentiment phrases. This study proposes an ensemble feature model for tweets with fuzzy sentiment, combining lexical, word-type, semantic, positional, and polarity-aware features. Tests on real data show improved performance, particularly in F1 score, indicating that modeling contextual sentiment and positional cues helps classify ambiguous tweets more accurately. **[8]**

Kasri et al. (2022), Standard word embeddings can blur sentiment because words with similar contexts may have opposite polarity, hurting sentiment classification. This paper proposes Continuous Sentiment Contextualized Vectors (CSCV), which learns sentiment-aware embeddings using surrounding context (CBOW) plus sentiment lexicons to inject polarity signals. It then combines CSCV vectors with existing pretrained embeddings using PCA to improve overall representation. Experiments report that CSCV-enhanced vectors can boost any pretrained embeddings, reduce "opposite polarity neighbors," and improve sentiment classification results. **[9]**

Schouten et al. (2016), This survey reviews aspect-level sentiment analysis, aiming to detect sentiment toward entities or their aspects for fine-grained insights. It summarizes strong progress in finding sentiment targets (entities/aspects) and associated polarity, and categorizes solutions by whether they handle aspect detection, sentiment classification, or both. The survey also groups approaches by algorithm type and reports each study's performance. It calls for standardized evaluation and shared datasets to enable fair comparison, and identifies concept-centric, semantically rich aspect-level methods as promising future directions. **[10]**

Durga et al. (2023), This paper proposes an integrated sentiment analysis framework combining large pretrained models and deep classifiers for e-commerce/social text. It uses BERT-large-cased (24 layers, 340M parameters) with fine-tuning (SGD) plus preprocessing, then applies BoW/Word2Vec feature extraction. The classification component is "deep sentiment analysis" with aspect-and-priority modeling via a Decision-based RNN. Experiments on Kaggle Twitter/Restaurant/Laptop datasets evaluate performance via confusion matrices and report improved outputs compared to existing methods. **[11]**

Tang et al. (2016), Traditional embeddings ignore sentiment signals, placing antonyms like *good* and *bad* close in vector space. This work proposes sentiment-specific word embeddings that encode both context and sentiment evidence, trained with neural networks and tailored loss functions on large corpora automatically labeled with sentiment cues (e.g., emoticons). The resulting embedding space keeps semantically similar words close while favoring same-polarity neighbors. Experiments show these embeddings outperform context-only embeddings across tasks like word-level sentiment, sentence classification, and sentiment lexicon building. **[12]**

Nazir et al. (2022), With rising social-media feedback, aspect-based sentiment analysis now focuses not only on extracting aspects and classifying their sentiments, but also on how sentiments evolve over time. This survey highlights issues such as aspect extraction, mapping relations among aspects, modeling dependencies and contextual-semantic interactions, and predicting sentiment evolution dynamics. It reviews recent work grouped by contributions to aspect extraction, aspect sentiment analysis, or sentiment evolution, and reports quantitative performance where available. It concludes with critical future research directions for improving aspect-level sentiment accuracy. **[13]**

Wu et al. (2019), Chinese microblog sentiment analysis using dictionaries is challenging due to limited sentiment-word coverage. This paper proposes constructing multiple dictionaries (base sentiment, emoji, and other related dictionaries), including a novel "new word" sentiment dictionary for microblogs. It also introduces semantic rule sets (inter-sentence and sentence-pattern rules) and an algorithm that computes sentiment from complex sentences to clauses to words, integrating emoji signals. Experiments show improved classification into positive, negative, and neutral microblogs. **[14]**

Table 1. Systematic literature review

Ref	Author (First author et al.)	Year	Title	Methods	Result	Advantage	Limitation
1	Obiedat et al.	2021	Arabic Aspect-Based Sentiment Analysis: A Systematic Literature Review	Systematic literature review of ABSA methods/datasets (2015–2021)	Reviewed 21 articles; highlights scarcity of annotated datasets and limited domains	Consolidates Arabic ABSA research and datasets; identifies key gaps	No new model/experiments; progress constrained by dataset scarcity
2	Xu et al.	2019	Chinese Text Sentiment Analysis Based on Extended Sentiment Dictionary	Extended sentiment dictionary (basic + domain + polysemic words) + Naive Bayes to infer field for polysemic words; sentiment scoring rules	Improves sentiment analysis feasibility/accuracy (exact metric not specified in your summary)	Better coverage of sentiment words + handles polysemy via field detection	Dictionary construction/maintenance effort; performance metrics not explicitly stated
3	Liu et al.	2022	Weight Distributing Method Combining Sentiment Dictionary and TF-IDF for Text Sentiment Analysis	Hybrid weighting combining lexicon-based sentiment dictionary + TF-IDF-style weighting	Accuracy up to **82.1%**; +13.9% vs lexicon-only; +7.7% vs TF-IDF weighting	Highlights sentiment-bearing words while retaining text information	Still depends on lexicon quality and weighting rules; generalization not detailed
4	Wang et al.	2020	SentiDiff: Combining Textual Information and Sentiment Diffusion Patterns for Twitter Sentiment Analysis	Fusion of tweet text + sentiment diffusion patterns; analyzes sentiment reversal; iterative algorithm (SentiDiff)	PR-AUC improvement **5.09–8.38%** vs text-only baselines	Uses diffusion/social patterns to improve short/ambiguous tweet analysis	Requires diffusion/network signals; may not apply where diffusion data unavailable
5	Poria et al.	2023	Beneath the Tip of the Iceberg: Current Challenges and New Directions in Sentiment Analysis Research	Perspective/review paper outlining shortcomings, under-explored aspects, and research directions	Identifies maturity misconceptions and open problems (no numeric results)	Strong conceptual roadmap; highlights overlooked challenges	No experimental validation; broad discussion rather than method evaluation
6	Yang et al.	2022	Affective Knowledge Augmented Interactive GCN for Chinese-Oriented ABSA	Knowledge-aware ABSA: affective commonsense knowledge + interactive GCN; MHSA for richer features; multilingual (Chinese+English) evaluation	Outperforms or approaches SOTA across multiple Chinese and English datasets (no exact metric in your summary)	Injects affective knowledge; works across Chinese & English datasets	Complexity and reliance on external affective knowledge; metrics not stated in your summary
7	Li et al.	2020	Sentiment Analysis of Danmaku Videos Based on Naïve Bayes and	Builds danmaku sentiment dictionary + Naive Bayes; sentiment scoring; visualization across	Significant effect on sentiment score and polarity detection (no exact	Tailored to danmaku; includes temporal sentiment	Domain-specific; effectiveness depends on dictionary coverage

			Sentiment Dictionary	seven sentiment dimensions	metric in summary)	distribution analysis	
8	Phan et al.	2020	Improving Tweet SA With Feature Ensemble Model for Fuzzy Sentiment	Feature ensemble incorporating lexical, semantic, word-type, position, sentiment polarity; focuses on fuzzy sentiment phrases	Improved tweet SA performance in terms of F1 score (exact value not specified)	Rich feature fusion captures sentiment context and position	Requires feature engineering; may be sensitive to preprocessing choices
9	Kasri et al.	2022	Refining Word Embeddings With Sentiment Information for Sentiment Analysis	Sentiment-aware embedding refinement; sentiment lexicons + CBOW; combine with pre-trained vectors via PCA	Improves sentiment classification; alleviates "similar vectors opposite polarity" issue	Enhances embeddings for sentiment; transferable to other pre-trained vectors	Needs sentiment lexicons; extra training/combination step
10	Schouten et al.	2016	Survey on Aspect-Level Sentiment Analysis	Survey of aspect detection and sentiment methods; categorizes solutions; calls for shared datasets/evaluation standardization	Provides state-of-art overview and reported performances (per study)	Comprehensive ABSA taxonomy; emphasizes evaluation standardization	No new model; conclusions depend on included studies
11	Durga et al.	2023	Deep-Sentiment: Deep SA Using Decision-Based RNN (D-RNN)	Integrated model using BERT-large-cased fine-tuning + BoW/Word2Vec features + Decision-based RNN; evaluated on Twitter/Restaurant/Laptop datasets	Demonstrates effectiveness vs existing methods (exact metrics not specified in your summary)	Combines pretrained transformers + deep model; multi-dataset evaluation	High compute; details/metrics not provided in your summary
12	Tang et al.	2016	Sentiment Embeddings With Applications to Sentiment Analysis	Learns sentiment-specific embeddings using context + sentiment supervision (e.g., emoticons); neural nets + tailored loss	Consistently outperforms context-only embeddings on multiple benchmarks (no exact metric in summary)	Reduces "good/bad near neighbors" problem; minimal feature engineering	Requires sentiment signals/large data; embedding training overhead
13	Nazir et al.	2022	Issues and Challenges of Aspect-Based Sentiment Analysis: A Comprehensive Survey	Survey focusing on aspect extraction, aspect sentiment, sentiment evolution; discusses interactions/dependencies/context	Summarizes progress; provides reported performance across reviewed studies	Strong coverage of ABSA challenges; clear future directions	No new experiments; dependent on reviewed literature
14	Wu et al.	2019	Chinese Micro-Blog SA Based on Multiple Dictionaries and Semantic Rules	Multiple sentiment dictionaries (incl. emoji + new-word dictionary) + semantic rule sets; clause-to-word sentiment calculation	Improves Chinese micro-blog sentiment classification accuracy (exact metric not stated in summary)	Increases sentiment-word coverage; handles emojis + complex sentence rules	Rule/dictionary maintenance effort; portability to other domains unclear

3. Research Gap

Based on Table 1, a major research gap is the lack of robust, generalizable sentiment analysis frameworks that work consistently across domains, languages, and text types, because many studies are either survey-based or focus on narrow, domain-specific settings such as Twitter diffusion, danmaku comments, or Chinese microblogs, limiting transferability to other real-world web texts (Obiedat et al., 2021; Li et al., 2020; Wang et al., 2020). Another gap is the insufficient availability of high-quality annotated datasets, especially for aspect-based sentiment analysis (ABSA) in under-resourced languages like Arabic, which constrains model training and benchmarking (Obiedat et al., 2021). In addition, several approaches depend heavily on lexicons, handcrafted rules, or feature engineering, which improves coverage and interpretability but raises maintenance issues and weakens adaptability to evolving language use and polysemy (Xu et al., 2019; Wu et al., 2019; Liu et al., 2022). Although deep learning, knowledge-augmented GCNs, and sentiment-aware embeddings show promise, their evaluation is often inconsistent and not standardized across shared benchmarks, making fair comparison difficult and reinforcing the need for unified evaluation protocols and cross-domain testing (Schouten et al., 2016; Nazir et al., 2022; Yang et al., 2022; Tang et al., 2016; Poria et al., 2023).

4. Systematic result analysis

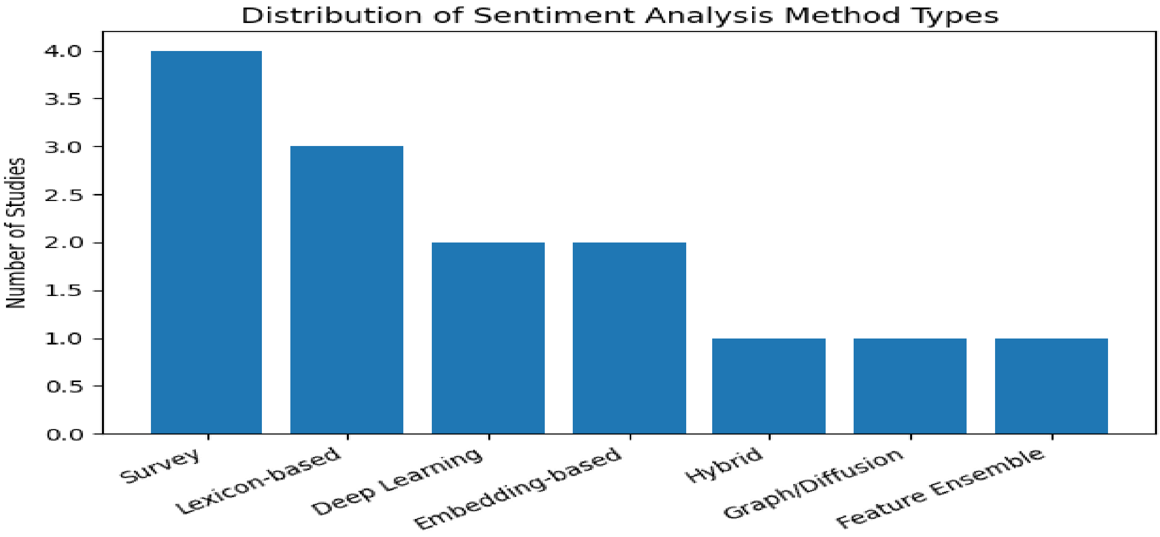

Figure 1: Distribution of Sentiment Analysis Method Types

Figure 1 illustrates the distribution of sentiment analysis methods used across the reviewed studies. It is evident that survey-based and lexicon-based approaches dominate literature, reflecting the foundational role of reviews and rule-driven techniques in sentiment analysis research. Deep learning and embedding-based methods appear less frequently, indicating that although advanced models are gaining traction, their adoption remains limited compared to traditional approaches. Hybrid, graph-based, and feature ensemble techniques are used sparingly, highlighting an opportunity for further exploration of integrated and structure-aware models.

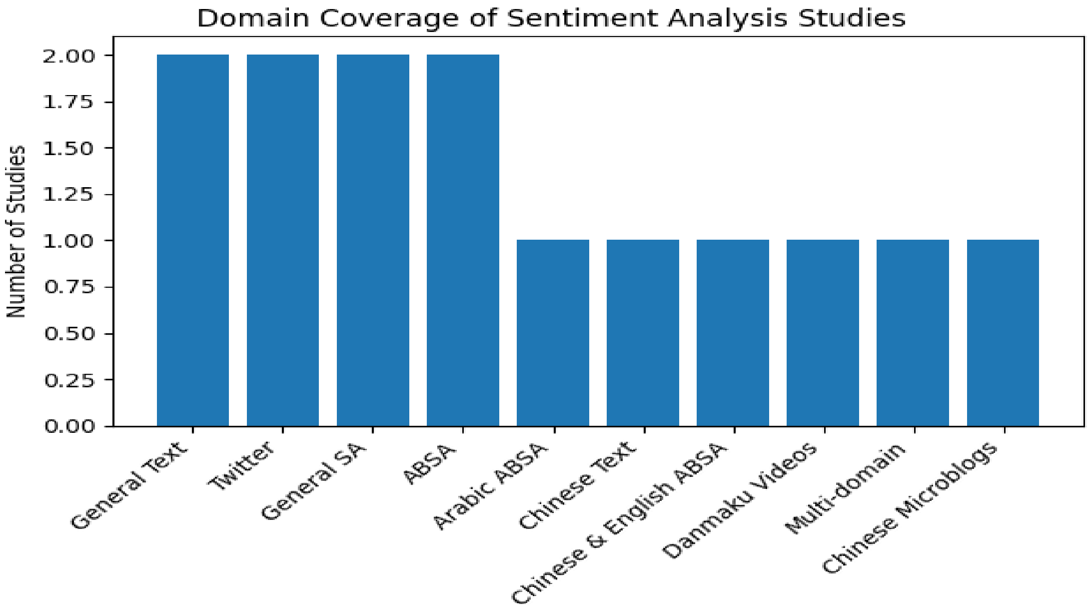

Figure 2: Domain Coverage of Sentiment Analysis Studies

Figure 2 presents the domain-wise distribution of sentiment analysis research. Most studies focus on general text and Twitter data, emphasizing the popularity of social media as a sentiment-rich data source. Fewer studies address language-specific and domain-specific datasets, such as Arabic ABSA, Chinese microblogs, and Danmaku videos. This uneven distribution reveals a research imbalance and underscores the need for more diversified datasets and domain-independent sentiment analysis frameworks.

5. Conclusion

This study presented a comprehensive comparative analysis of sentiment analysis methods applied to web and social media texts, emphasizing lexicon-based techniques, machine learning models, and deep learning approaches. The review highlights that lexicon-based methods are efficient and interpretable but limited by vocabulary coverage and adaptability. Machine learning approaches offer improved performance but rely heavily on feature engineering and domain-specific training data. Deep learning models achieve superior accuracy by capturing contextual and semantic nuances, yet they demand large, annotated datasets, high computational resources, and often lack transparency. Furthermore, the analysis reveals persistent challenges, including dataset scarcity for under-resourced languages, poor cross-domain generalization, difficulty in handling implicit sentiments, and the absence of standardized evaluation benchmarks. Addressing these limitations is critical for building robust and scalable sentiment analysis systems capable of real-world deployment. Future research should focus on developing unified, multilingual, and domain-adaptive sentiment analysis frameworks that combine interpretability, efficiency, and contextual understanding using hybrid and explainable AI models.

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