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A Systematic Review and Classification of Sentiment Analysis Approaches

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ABSTRACT:

In fields including social media analytics, politics, marketing, and healthcare, sentiment analysis—also referred to as opinion mining—has become an essential tool for comprehending public attitude. The field of sentiment analysis techniques is still broad and dispersed, even with the quick advancement of computer tools in this area. This study offers a thorough examination and categorization of current sentiment analysis methodologies, encompassing lexicon-based strategies, contemporary deep learning models, and conventional machine learning approaches. Data sources, feature extraction techniques, language resources, and sentiment classification levels (document, sentence, aspect-level) are the categories by which we group these methods. The review also addresses multilingual sentiment analysis, challenges like sarcasm detection and domain adaptation, and evaluates the performance metrics used across studies. By identifying research trends and gaps, this review offers a comprehensive framework to guide future research and application development in sentiment analysis.

KEYWORDS: Semantic Analysis, Sentiment Polarity Detection, Social Media Analytics

INTRODUCTION:

Large volumes of user-generated material are created every day on platforms like social media, blogs, and review websites in the age of digital communication. Because of the abundance of thoughts and feelings in this data, sentiment analysis (SA), sometimes referred to as opinion mining, is an essential technique for comprehending societal trends, consumer behavior, and public sentiment. The goal of sentiment analysis is to locate, extract, and categorize subjective information from textual data, usually classifying it as neutral, negative, or positive [1].

Businesses use SA for trend research, decision-making, and customer interaction in a variety of industries, including marketing, politics, finance, and healthcare. Because sentiment analysis is an interdisciplinary field, methods have developed into three main categories: machine learning-based techniques, which employ algorithms trained on annotated corpora; lexicon-based techniques which rely on predefined sentiment dictionaries; and hybrid models, which combine the advantages of both [2]. Recent advancements in Natural Language Processing (NLP) and Deep Learning (DL) have significantly enhanced the accuracy and scalability of sentiment classification tasks. However, the proliferation of methods has led to inconsistencies in performance evaluation, applicability across domains, and adaptability to evolving language constructs [3]. This paper aims to provide a systematic review and classification of sentiment analysis approaches, offering a structured overview of their principles, comparative performance, and application contexts. By categorizing the methods and highlighting their respective strengths and limitations, this study seeks to inform researchers and practitioners about the current landscape and potential research directions in sentiment analysis.

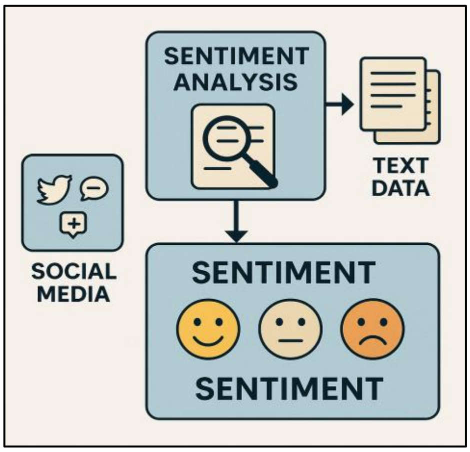

Figure 1: An instance of Sentiment Analysis through social media

Research Background:

Over the past 20 years, the proliferation of opinion-rich content on websites like Facebook, Twitter, Amazon, and TripAdvisor has led to a notable expansion in the discipline of sentiment analysis, or SA. Many computational methods for assessing and categorizing text sentiment have emerged as a result of the growing need to comprehend this subjective data. Sentiment analysis was once dominated by lexicon-based techniques, which used manually or mechanically selected dictionaries of words with predetermined sentiment scores. Although many techniques, like SentiWordNet [4], produced clear and understandable models, they had trouble with domain adaptability and context sensitivity. At first, lexicon-based approaches—which used manually or mechanically selected dictionaries of terms with predetermined sentiment scores—dominated sentiment analysis. Though they grappled with context sensitivity and domain adaptability, several techniques like Sent WordNet [3] provided transparent and interpretable models.

More reliable models that taught sentiment categorization from labeled datasets surfaced with the introduction of machine learning (ML). For binary and multi-class sentiment classification problems, classical machine learning methods like Naive Bayes, Support Vector Machines (SVM), and Logistic Regression have gained popularity [5]. These techniques needed a lot of feature engineering and labeled data, but they showed better accuracy than lexicon-based models. By allowing models to learn hierarchical depictions of text without the need for manual feature extraction, deep learning greatly improved sentiment analysis. Long Short-Term Memory (LSTM) networks, recurrent neural networks (RNNs), and more lately Transformers like BERT [6] have demonstrated impressive ability in processing complicated phrase patterns, sarcasm, and context. Modern sentiment analysis systems currently rely heavily on these models.

The rise of hybrid models, which combine lexicon-based approaches with machine learning or deep learning to capitalize on their complementing advantages, is another noteworthy trend. For instance, in semi-supervised learning settings, lexicons can be employed to improve feature representation or offer a lack of strong supervision [7]. The paper [8] provides a comprehensive examination of sentiment analysis methodologies, encompassing both traditional and state-of-the-art deep learning systems. They discuss the issues with sentiment analysis, such as context-dependency, ambiguity, and sarcasm, and we examine the ways in which different approaches address these issues. Additionally, this article delves into a variety of sentiment analysis applications across industries like politics, marketing, healthcare, and customer service.

There is now an unparalleled amount of user-generated content, full of viewpoints and emotional expression, thanks to the growth of social media sites like Facebook, YouTube, Reddit, and Twitter. It is now more important than ever to analyze this content to determine public mood for use in crisis management, political forecasting, public health surveillance, and brand monitoring [9]. Because of its casual language, short text length, slang, emoticons, sarcasm, and code-mixing, social media sentiment analysis poses special difficulties. Social media data frequently contains dynamic language and lacks grammatical coherence, unlike traditional text (such as news stories or product evaluations), which impairs the effectiveness of typical sentiment analysis techniques [10].

In order to overcome these obstacles, researchers have looked into domain adaptation strategies, which try to move models that have been trained on one domain—like product reviews—to another like tweets without suffering appreciable performance loss. Since annotated sentiment data is frequently lacking in new or specialized areas, domain adaptation is essential to avoiding ineffective and expensive retraining. Feature alignment or instance reweighting were the mainstays of early domain adaptation techniques. More recently, by learning domain-invariant representations, deep transfer learning and domain-adversarial neural networks (DANNs) have demonstrated impressive performance in adapting sentiment models across domains [11]. Cross-domain sentiment categorization has been further enhanced by pretrained language models such as BERT, RoBERTa, and XLNet, particularly when adjusted with minimal in-domain input.

SENTIMENT CLASSIFICATION LEVELS:

Sentiment analysis can be applied at different granularities depending on the application or the data type. The three primary levels are:

1. **Document-Level Sentiment Analysis:** This approach classifies the overall sentiment expressed in an entire document (e.g., a full review, blog post, or tweet) as positive, negative, or neutral. The document contains opinions about a single entity or topic [12].
2. **Sentence-Level Sentiment Analysis:** This level focuses on determining the sentiment of individual sentences rather than the entire document. To identify sentiment polarity at finer granularity, especially when a document has mixed sentiments across sentences [13].
3. **Aspect-Level Sentiment Analysis (Aspect-Based Sentiment Analysis or ABSA):** This level identifies specific aspects or features of an entity mentioned in the text and determines the sentiment expressed toward each aspect. To extract fine-grained opinions and gain deeper insights [14].

Table 1: Comparative analysis of Sentiment levels:

Level	**Unit of Analysis**	**Granularity**	**Strengths**	**Limitations**
Document-Level	Whole document	Coarse	Easy to implement, fast	Misses' internal sentiment diversity
Sentence-Level	Individual sentence	Medium	Captures sentence-wise polarity	Loses context, ambiguity
Aspect-Level	Entity features	Fine	Highly informative, business insights	Complex, needs entity-aspect linkage

Multilingual Sentiment Analysis (MSA):

The technique of identifying and categorizing sentiments conveyed in texts written in various languages is known as multilingual sentiment analysis, or MSA. It seeks to extend conventional sentiment analysis, which was primarily created for English, to international settings where people express their ideas in a variety of languages, including low-resource and code-mixed languages. Social media platforms (like Twitter, Facebook, YouTube) attract users from diverse linguistic backgrounds.

1. **Translation-Based Approach:** Translate non-English text to English using tools (e.g., Google Translate), then apply English sentiment classifiers [15].
2. **Language-Specific Classifiers:** Train separate models for each language using annotated datasets [16].
3. **Cross-Lingual Embeddings:** Use shared multilingual word embeddings (e.g., MUSE, fastText, LASER) to represent words across languages in a common space. Models trained in one language (e.g., English) can be adapted to others [17].
4. **Multilingual Pretrained Transformers:** Use models like mBERT, XLM-RoBERTa, or RemBERT trained on 100+ languages. Fine-tuning these models on multilingual sentiment datasets yields strong performance.

Table 2: Comparison of Multilingual Sentiment Analysis Methods

Approach	Strengths	Limitations
Translation-Based	Simple, uses English resources	Context/sentiment loss in translation
Language-Specific	Preserves cultural meaning	Not scalable to many languages
Cross-Lingual Embeddings	Shared space, reusable	Still requires alignment effort
Multilingual Transformers	High accuracy, zero-shot transfer	High computational cost

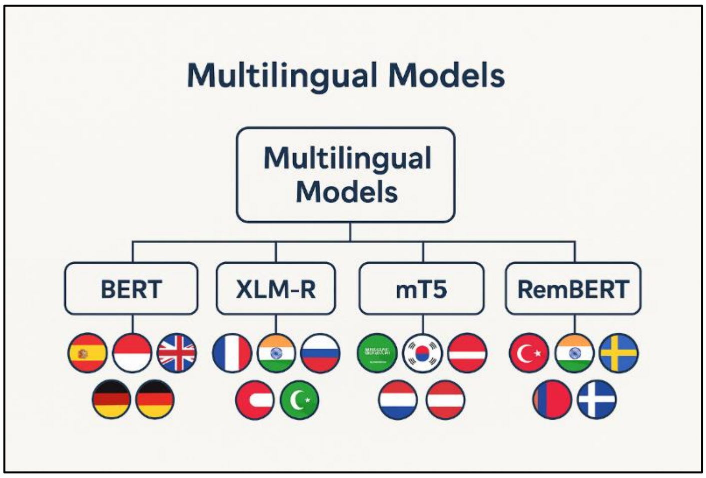

Figure 2: examples if Multilingual Models

Latest developments in sentiment analysis methods:

1. **Transformer-Based Models and Fine-Tuning:** Models like BERT, RoBERTa, XLNet, and DeBERTa have become mainstream. Domain-specific BERTs such as FinBERT (finance), BioBERT (healthcare), and Sentiment RoBERTa have been pretrained for high precision in sentiment-rich domains. Prompt-based fine-tuning and instruction tuning have improved zero-shot and few-shot sentiment classification capabilities [19].
2. **Multilingual and Cross-Lingual Sentiment Models:** Models like XLM-RoBERTa, mT5, and RemBERT handle over 100 languages with high accuracy. Cross-lingual sentiment transfer is now more feasible using zero-shot transfer and adapter layers. Enhanced support for code-mixed and low-resource languages via transfer learning and transliteration models [20].
3. **Aspect-Based Sentiment Analysis (ABSA) 2.0:** Shift from manual aspect extraction to end-to-end deep ABSA using sequence tagging + classification. Use of graph neural networks (GNNs) and dependency trees to model context-aware sentiment across aspects. Integration of Sentiment Role Labeling (SRL) and Joint Entity-Aspect-Sentiment extraction [21].
4. **Sarcasm, Irony, and Emotion Detection:** Use of multimodal sentiment analysis (text + image/video + audio) for sarcasm/emotion detection. Training on emotion-enriched datasets using contrastive learning to differentiate literal vs. sarcastic tones [22].
5. **Sentiment Analysis with Large Language Models (LLMs):** Use of ChatGPT, Claude, LLaMA, and Gemini for sentiment analysis via instruction prompting. No need for fine-tuning; prompt engineering gives competitive performance in zero-shot settings. Chain-of-thought reasoning and multi-turn context tracking enhance subjective sentiment understanding [23].

6. **Explainable Sentiment Analysis (XSA):** Increasing focus on interpretable AI in sentiment systems. Use of attention visualization, layer-wise relevance propagation (LRP), and SHAP/LIME for model transparency. Industry adoption in finance and healthcare where interpretability is crucial [24].
7. **Sentiment Analysis with Structured & Real-Time Data:** Streaming sentiment analysis for real-time data from social media, financial news, or IoT devices. Use of incremental transformers and sliding window models. Integration with event detection, trend forecasting, and fake sentiment detection [25].

Table 3: Comparative study of latest Developments

Area	Advancement	Models/Tools
Transformers & Fine-tuning	Domain-specific BERTs, prompts	BERT, RoBERTa, DeBERTa, FinBERT
Multilingual Models	Cross-lingual zero-shot, adapters	XLM-R, mT5, RemBERT
Aspect-Level Sentiment	Graph & joint models	GCNs, GATs, JointABSA
Sarcasm & Emotion Detection	Multimodal and emotion-rich embeddings	EmoBERTa, multimodal GNNs
LLMs & prompting	Zero-shot sentiment with LLMs	ChatGPT, Claude, LLaMA
Explainable Sentiment	Attention + SHAP/LIME	XAI tools, LRP, captum
Real-Time Sentiment Systems	Streaming-ready models	Incremental BERT, SLIDE, FastBERT

CONCLUSION

Sentiment analysis is evolving rapidly with multilingual understanding, LLMs, aspect extraction, and explain ability becoming central. The future of sentiment systems is context-aware, cross-lingual, emotion-sensitive, and deeply human-aligned. Sentiment analysis has undergone a remarkable evolution, moving from simple rule-based systems to highly sophisticated deep learning and multilingual models. Each level of sentiment classification—document-level, sentence-level, and aspect-level—serves unique analytical purposes, ranging from broad sentiment scoring to fine-grained opinion mining. Early methods such as lexicon-based and traditional machine learning classifiers laid the groundwork for computational sentiment extraction. These were later surpassed by neural network models, particularly RNNs, LSTMs, and eventually transformer-based architectures like BERT and RoBERTa, which significantly enhanced context understanding and accuracy. With globalization and the rise of user-generated content in multiple languages, multilingual sentiment analysis has become essential. The advent of powerful models such as mBERT, XLM-R, mT5, and RemBERT has enabled cross-lingual sentiment understanding and transfer learning across low-resource and code-mixed languages. Additionally, innovations in aspect-based sentiment analysis (ABSA), emotion detection, sarcasm handling, and real-time sentiment monitoring have further expanded the applicability of sentiment analysis in diverse domains such as healthcare, finance, and public policy. The integration of Large Language Models (LLMs) like ChatGPT and instruction-based prompting marks a new phase where sentiment tasks can be solved with minimal labeled data. At the same time, the emphasis on explainability, trust, and ethical AI has led to the incorporation of interpretability frameworks like SHAP and LIME.

In conclusion, sentiment analysis today is a multi-layered, multilingual, and increasingly intelligent discipline. While significant progress has been made, ongoing challenges such as sarcasm detection, cultural context, code-mixing, and domain adaptability continue to offer rich opportunities for future research and practical deployment.

REFERENCES

1. Liu, B. (2012). Sentiment analysis and opinion mining. Synthesis Lectures on Human Language Technologies, 5(1), 1–167.
2. Cambria, E., Schuller, B., Xia, Y., & Havasi, C. (2013). New avenues in opinion mining and sentiment analysis. IEEE Intelligent Systems, 28(2), 15–21.
3. Zhang, L., Wang, S., & Liu, B. (2018). Deep learning for sentiment analysis: A survey. Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery, 8(4), e1253.
4. Esuli, A., & Sebastiani, F. (2006). SentiWordNet: A publicly available lexical resource for opinion mining. Proceedings of LREC.
5. Pang, B., Lee, L., & Vaithyanathan, S. (2002). Thumbs up? Sentiment classification using machine learning techniques. Proceedings of the ACL-02 conference on Empirical methods in natural language processing, 79–86.
6. Devlin, J., Chang, M.-W., Lee, K., & Toutanova, K. (2019). BERT: Pre-training of deep bidirectional transformers for language understanding. Proceedings of NAACL-HLT, 4171–4186.
7. Zhou, K., Huang, H., Yang, Y., & Deng, Y. (2020). A survey on sentiment analysis in social media: Techniques, applications, and challenges. Information Fusion, 64, 49–65.
8. Rahul Sagar, Sumit Dalal, Rohini Sharma, Sumiran, "Classification of Sentiment Analysis Techniques: A Comprehensive Approach, " International Journal of Advanced Research in Arts, Science, Engineering & Management (IJARASEM), Volume 11, Issue 2, March 2024, pp. 5200-5205.

9. Giachanou, A., & Crestani, F. (2016). Like it or not: A survey of Twitter sentiment analysis methods. ACM Computing Surveys (CSUR), 49(2), 1–41.

10. Kumar, A., & Jaiswal, A. (2020). A survey on sentiment analysis and opinion mining in social media. Journal of Emerging Technologies and Innovative Research, 7(6), 442–448.

11. Glorot, X., Bordes, A., & Bengio, Y. (2011). Domain adaptation for large-scale sentiment classification: A deep learning approach. Proceedings of the 28th International Conference on Machine Learning (ICML), 513–520.

12. Pang, B., & Lee, L. (2008). Opinion mining and sentiment analysis. Foundations and Trends® in Information Retrieval, 2(1–2), 1–135.

13. Wilson, T., Wiebe, J., & Hoffmann, P. (2005). Recognizing contextual polarity in phrase-level sentiment analysis. Proceedings of HLT/EMNLP, 347–354.

14. Pontiki, M. et al. (2016). SemEval-2016 Task 5: Aspect Based Sentiment Analysis. Proceedings of SemEval-2016, 19–30.

15. Balahur, A., et al. (2014). Comparative experiments using supervised learning and machine translation for multilingual sentiment analysis. Computer Speech & Language, 28(1), 56–75.

16. Mihalcea, R., Banea, C., & Wiebe, J. (2007). Learning multilingual subjective language via cross-lingual projections. ACL 2007.

17. Conneau, A., et al. (2020). Unsupervised cross-lingual representation learning at scale. ACL 2020.

18. Pires, T., Schlinger, E., & Garrette, D. (2019). How multilingual is Multilingual BERT? ACL 2019.

19. Liu et al. (2023). Domain-specific transformer-based sentiment classification using prompt-tuned RoBERTa. ACL Findings.

20. Singh et al. (2024). Cross-lingual sentiment analysis with unified transformer adapters. EMNLP 2024.

21. Zhang et al. (2023). Joint Aspect and Sentiment Extraction via Dependency-Augmented Graph Attention Networks. AAAI 2023.

22. Li et al. (2024). Emotion-enhanced Transformers for Sarcasm and Sentiment Understanding. COLING 2024.

23. Zhao et al. (2023). Sentiment analysis with ChatGPT: Zero-shot vs fine-tuned models. arXiv preprint arXiv:2304.14161.

24. Ribeiro et al. (2023). Trustworthy and explainable sentiment classification with model-agnostic methods. IJCAI 2023.

25. Wang et al. (2024). Real-time sentiment stream analysis using adaptive transformer architectures. KDD 2024.