

A Comprehensive Review of Sentiment Analysis and Aspect-Based Sentiment Analysis: Methods, Data Sources, and Open Research Challenges

Erugu Krishna¹, Dr. Sonawane Vijay Ramnath²

¹Research Scholar, ²Research Supervisor

^{1,2}Dr. A. P. J. Abdul Kalam University, Indore, India

krishna.cseit@gmail.com, vijaysonawane11@gmail.com

Presented at **International Conference on Engineering, Economics, Management and Applied Sciences (ICE2MAS-24)**, Bangkok, 21-24 December 2024, organized by **Academy of Art, Science and Technology (AAST)**.



Published in IJIRMP (E-ISSN: 2349-7300), ICE2MAS-24

License: [Creative Commons Attribution-ShareAlike 4.0 International License](https://creativecommons.org/licenses/by-sa/4.0/)



Abstract

Sentiment Analysis (SA) and Aspect-Based Sentiment Analysis (ABSA) have emerged as essential research areas within natural language processing due to the exponential growth of user-generated content on web and social media platforms. These techniques aim to automatically extract, interpret, and classify opinions expressed in textual data, enabling organizations and researchers to understand public perceptions at both coarse and fine-grained levels. This paper presents a comprehensive review of existing sentiment analysis and ABSA approaches, covering traditional lexicon-based methods, classical machine learning algorithms, deep learning models, and recent advances involving transfer learning, contextual embeddings, and multimodal analysis. The study systematically analyzes commonly used data sources, including e-commerce reviews, social media posts, blogs, and multimodal datasets, highlighting their strengths and limitations. Furthermore, the review identifies key challenges such as domain dependency, scarcity of annotated datasets for low-resource languages, handling implicit and context-dependent sentiments, and limited generalization across domains and modalities. By synthesizing findings from recent literature, this paper outlines open research challenges and provides insights into future research directions aimed at developing more robust, scalable, and context-aware sentiment analysis systems.

Keywords: Sentiment Analysis, Aspect-Based Sentiment Analysis, Opinion Mining, Machine Learning, Deep Learning, Multimodal Analysis

1. Introduction

The rapid expansion of the internet and social media platforms has fundamentally transformed how individuals express opinions, share experiences, and influence decision-making processes. User-generated content in the form of reviews, comments, tweets, blogs, and multimedia posts has become a rich source of information reflecting public sentiment across diverse domains such as e-commerce, healthcare, politics, tourism, education, and entertainment. Extracting meaningful insights from this vast amount of unstructured textual data has become a critical task, giving rise to the field of Sentiment Analysis (SA), also known as opinion mining [1].

Sentiment analysis focuses on identifying the polarity of opinions expressed in text, typically categorizing them as positive, negative, or neutral. Early approaches to sentiment analysis relied heavily on lexicon-

based methods, where predefined sentiment dictionaries were used to determine the emotional orientation of words and phrases. While such approaches are simple and interpretable, they often struggle with context sensitivity, domain dependency, sarcasm, negation, and polysemy. These limitations led to the adoption of machine learning techniques, including Naïve Bayes, Support Vector Machines, Decision Trees, and K-Nearest Neighbors, which treat sentiment analysis as a supervised classification problem. These models demonstrated improved performance but required extensive feature engineering and large labeled datasets [2].

As sentiment analysis matured, researchers recognized that document-level or sentence-level polarity classification often fails to capture fine-grained opinions directed toward specific features or aspects of an entity. This realization led to the emergence of Aspect-Based Sentiment Analysis (ABSA), which aims to identify aspects within text and determine the sentiment associated with each aspect individually. ABSA enables a more detailed understanding of user opinions, such as distinguishing between positive sentiment toward a product's performance and negative sentiment toward its price. However, ABSA introduces additional challenges, including aspect extraction, aspect-sentiment association, and handling implicit aspects [3].

The advancement of deep learning has significantly influenced both SA and ABSA research. Neural network models such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM) networks, and attention mechanisms have been widely adopted to automatically learn semantic and sentiment representations from data. More recently, transformer-based models such as BERT and its variants have achieved state-of-the-art performance by capturing contextualized word representations. Additionally, hybrid models integrating sentiment lexicons with deep learning architectures have shown promise in enhancing sentiment awareness [4].

Despite these advances, several challenges persist. Many sentiment analysis models suffer from domain dependency and limited generalization across datasets. The scarcity of annotated data for low-resource languages further restricts progress. Moreover, emerging research areas such as implicit sentiment detection, cross-domain learning, multimodal sentiment analysis, and explainability remain underexplored. Addressing these challenges is essential for building robust and reliable sentiment analysis systems [5].

This paper provides a comprehensive review of sentiment analysis and aspect-based sentiment analysis methods, data sources, and open research challenges. By synthesizing recent literature, this study aims to offer a clear understanding of current trends and identify directions for future research.

2. Literature review

Wang et al. (2021), Existing sentiment-embedding approaches often inject lexicon polarity into word vectors but fail to capture context-dependent sentiment for the same word. This paper proposes using “sentiment concepts” to select the optimal concept for a word given its context (via Microsoft Concept Graph), then retrieve sentiment intensity from a multi-semantics lexicon constructed by the authors. It combines two refined embedding methods to produce richer representations. Tests on six datasets show the proposed concept-based embedding improve sentiment analysis compared with traditional and earlier sentiment-embedding baselines. [1]

Kim et al. (2021), Online review ratings and volume are common sentiment proxies but suffer from extremity bias (ratings skewed by very happy/unhappy reviewers) and ambiguity (volume may rise for many reasons). This article proposes text-mining alternatives and finds sentiment scores may be less prone to extremity bias than ratings: sentiment scores tend to be more normally distributed while ratings skew to extremes. It also suggests combining sentiment scores with review length to better capture customer enthusiasm and interpret “word of mouth” beyond star ratings. [2]

Smetanin et al. (2020), Sentiment analysis has been widely applied to English content, but Russian-language applications remain underexplored. This survey reviews applied sentiment analysis studies on

Russian texts, focusing on use cases rather than classification accuracy. Studies are systematically categorized by data source, application purpose, methods, outcomes, and limitations. The paper outlines challenges, proposes a future research agenda, and compiles publicly available Russian sentiment datasets to support researchers in dataset selection and methodological improvements. [3]

He et al. (2022), Aspect-Based Sentiment Analysis (ABSA) predicts sentiment polarity toward specific aspects and is a fine-grained NLP task. Existing methods mainly rely on local context and often ignore global contextual dependencies, with limited work on Chinese and multilingual ABSA. This paper proposes LGCF, a multilingual model that jointly learns local and global context–aspect correlations. Experiments on multiple Chinese and English benchmark datasets show LGCF outperforms state-of-the-art models, with ablation studies confirming each component’s effectiveness. [4]

Yang et al. (2020), To enhance sentiment analysis of Chinese e-commerce reviews, this paper introduces SLCABG, a hybrid model combining sentiment lexicons with CNN and attention-based BiGRU. The lexicon strengthens sentiment cues, CNN extracts key features, BiGRU captures contextual dependencies, and attention weights important information. Trained on over 100,000 cleaned book reviews from Dangdang.com, experimental results show improved sentiment classification performance, demonstrating the effectiveness of integrating lexicon knowledge with deep learning. [5]

Zhang et al. (2023), Aspect-level sentiment analysis remains challenging due to poor cross-domain transfer and weak modeling of aspect–sentiment word relations. This paper proposes Efficient Adaptive Transfer Network (EATN), which incorporates domain adaptation through a Domain Adaptation Module (DAM) and multiple-kernel learning to reduce domain discrepancy. An aspect-oriented multi-head attention mechanism captures direct aspect–sentiment associations. Experiments on six public datasets across domains show EATN achieves strong generalization and outperforms existing methods. [6]

Fu et al. (2018), Traditional LSTM-based sentiment models rely heavily on word embeddings that encode semantic but not sentiment information. To address this, this paper proposes a lexicon-enhanced LSTM, which integrates sentiment embeddings learned from sentiment lexicons with standard word embeddings. A novel attention mechanism captures global sentiment without requiring explicit targets. Experiments on English and Chinese datasets show the proposed model achieves comparable or superior performance to existing sentiment analysis models. [7]

Kastrati et al. (2020), Analyzing student feedback manually is impractical for large-scale online education platforms such as MOOCs. This paper proposes a framework using aspect-level sentiment analysis with weak supervision to automatically analyze student reviews. Weakly annotated MOOC aspects are propagated to unlabeled data, reducing dependence on costly manual labels. Experiments on large Coursera and classroom datasets show strong performance in aspect identification and sentiment classification, outperforming fully supervised approaches. [8]

Al-Moslmi et al. (2017), Cross-domain sentiment analysis is challenging due to the lack of universally annotated datasets. This systematic review analyzes studies published between 2010–2016 that address cross-domain sentiment classification. It compares techniques such as domain adaptation, feature alignment, and transfer learning, concluding that no single method fully solves the problem. The review serves as a consolidated resource to guide researchers in developing more robust and accurate cross-domain sentiment analysis approaches. [9]

Deng et al. (2019), Sentiment lexicon construction using deep learning often ignores word importance in determining document polarity. This paper proposes Sparse Self-Attention LSTM (SSALSTM) to capture word importance via self-attention with L1 regularization, ensuring sparsity. The learned sentiment-aware embeddings are used to build large-scale Twitter sentiment lexicons. Experiments on SemEval 2013–2016 datasets show the generated lexicons achieve state-of-the-art performance in both supervised and unsupervised sentiment classification. [10]

Huang et al. (2022), Lexicon-based methods ignore context, while supervised models often overlook sentiment-word knowledge. To address this, this paper proposes SentiCNN, which combines contextual information from word embeddings with sentiment cues from lexicons. A Highway Network adaptively fuses both information types, and lexicon-based attention mechanisms (LBAMs) highlight key sentiment indicators. Experiments on benchmark datasets confirm that sentiment words, attention, and hybrid modeling significantly improve sentiment classification accuracy. [11]

Su et al. (2024), Implicit aspect sentiment expressions lack explicit opinion words, making ABSA challenging in social media text. Existing dependency-tree and attention-based methods often miss relevant aspect sentiment or focus on irrelevant words. This paper proposes a **Prototype-based Demonstration (PD-ABSA)** model with prototype learning and demonstration stages. Mask-aware attention and contrastive learning capture implicit sentiment prototypes, which guide a T5 model via neural demonstrations. Experiments on Laptop and Restaurant datasets show consistent accuracy gains, especially for implicit sentiment cases, validating effectiveness in social computing scenarios. [12]

Alfreihat et al. (2024), Informal Arabic sentiment analysis is difficult due to morphology and dialects. This work introduces **Emo-SL**, an emoji sentiment lexicon for Arabic tweets, built from 58K emoji-containing tweets. Sentiment scores for 222 emojis are computed and integrated with text features. ML classifiers (SVM, NB, RF, KNN) trained with emoji-aware features significantly outperform text-only models, improving accuracy by 26.7% and achieving 89% F1. Results confirm emojis provide crucial contextual sentiment cues in noisy Arabic micro-text. [13]

Mahmoudi et al. (2024), This study evaluates popular sentiment analysis packages in Python and R, comparing accuracy and time complexity across seven datasets. Results show performance varies significantly by dataset, with **sentimentr** being the most consistent. Python tools are generally faster, but most packages struggle to model sentiment intensity and often overfit to familiar data. While effective for binary polarity, generalization to unseen datasets remains limited, highlighting the need for more robust and adaptable sentiment analysis tools. [14]

Wang et al. (2024), Aspect-based multimodal sentiment analysis (ABMSA) often ignores global sentiment tendency and fine-grained multimodal cues. This paper proposes a **Dual-Perspective Fusion Network (DPFN)** that combines global sentiment (via text–image captions) with local fine-grained information using graph structures over text and images. By integrating both perspectives, the model improves aspect-level sentiment prediction. Experiments on multimodal Twitter datasets demonstrate DPFN consistently outperforms state-of-the-art approaches. [15]

Zhao et al. (2024), Multimodal Aspect-Based Sentiment Analysis (MABSA) integrates text with other modalities to infer aspect sentiment. This survey systematically reviews recent MABSA research, introducing core concepts, summarizing methods for multimodal aspect classification and aspect–sentiment pair extraction, and comparing their strengths and weaknesses. It also reviews commonly used datasets, evaluation metrics, and reported results. Finally, it outlines emerging research trends, providing a structured reference for future MABSA studies. [16]

Ruan et al. (2024), Image sentiment analysis has largely focused on CNN-based content features, overlooking the psychological importance of color. This paper proposes **Color Enhanced Cross Correlation Net (CECCN)**, which jointly models image content and color features and their correlations. Content is extracted via pretrained CNNs, while color moments are derived from multiple color spaces. A cross-correlation mechanism with attention enhances sentiment cues. Experiments on benchmark datasets show CECCN outperforms existing image sentiment models. [17]

Razali et al. (2024), Understanding customer sentiment is vital for gastronomy tourism, yet traditional analysis is slow, subjective, and weak at handling imbalanced data. This research introduces a hybrid lexicon-based and ML approach with data augmentation, feature engineering, and visualization tailored for Sarawak’s gastronomy sector. Using synonym augmentation, n-grams, and kNN, the system achieves

0.98 accuracy and 0.99 F1/ROC-AUC. The framework significantly improves minority sentiment detection and supports real-time business intelligence. [18]

Table 1. Systematic literature review

Ref	Author (First author et al.)	Year	Title	Methods	Result	Advantage	Limitation	Data Used
1	Wang et al.	2021	Refined Global Word Embeddings Based on Sentiment Concept	Sentiment concept graph, sentiment-aware embeddings, PCA	Improved sentiment classification across 6 datasets	Handles contextual sentiment polarity	Relies on external concept graphs	Six benchmark sentiment datasets
2	Kim et al.	2021	Using Online Reviews for Customer Sentiment Analysis	Text mining, sentiment score analysis	Sentiment scores reduce extremity bias	Better representation of enthusiasm	Not predictive, mainly analytical	Online customer reviews
3	Smetanin et al.	2020	Applications of Sentiment Analysis for Russian Texts	Survey and dataset analysis	Identified gaps and challenges	Highlights under-resourced language issues	No experimental validation	Russian-language sentiment datasets
4	He et al.	2022	Local and Global Context Focus Model for ABSA	Multilingual deep learning (LGCF), attention	Outperformed SOTA on Chinese & English datasets	Captures local & global context	High computational cost	Chinese & English review datasets
5	Yang et al.	2020	Sentiment Analysis for Chinese E-Commerce Reviews	CNN + BiGRU + sentiment lexicon	Improved accuracy on large-scale data	Combines lexicon & DL strengths	Language-specific model	Dangdang.com book reviews
6	Zhang et al.	2023	EATN for Aspect-Level Sentiment Analysis	Transfer learning, DAM, multi-head attention	Strong cross-domain performance	Effective domain adaptation	Requires labeled source domains	Six public ABSA datasets
7	Fu et al.	2018	Lexicon-Enhanced LSTM with Attention	Sentiment lexicon + LSTM + attention	Competitive accuracy on EN & CN	Improved word sentiment representation	Dependent on lexicon quality	English & Chinese datasets
8	Kastrati et al.	2020	Weakly Supervised ABSA for MOOCs	Weak supervision, ABSA framework	High accuracy with reduced labeling	Reduces annotation cost	Aspect coverage limited	Coursera & classroom reviews
9	Al-Moslmi et al.	2017	Cross-Domain Sentiment Analysis Review	Systematic literature review	Identified no universal solution	Comprehensive method overview	No experimental comparison	Multiple sentiment datasets

10	Deng et al.	2019	Sparse Self-Attention LSTM for Lexicon Construction	SSALSTM, sparse attention, L1 regularization	SOTA lexicon performance	Highlights key sentiment words	Complex model training	SemEval 2013–2016
11	Huang et al.	2022	Lexicon-Based Sentiment CNN (SentiCNN)	CNN + lexicon attention + highway network	Improved sentence sentiment accuracy	Integrates context & sentiment	Limited dataset generalization	Online review datasets
12	Su et al.	2024	Prototype-Based Demonstration for ABSA	Contrastive learning, T5, prototypes	Accuracy gain up to 1.68%	Handles implicit sentiment well	Model complexity	Laptop & Restaurant datasets
13	Alfreihat et al.	2024	Emo-SL Framework for Arabic Tweets	Emoji sentiment lexicon + ML	89% F1-score	Captures emoji semantics	Emoji dependence	58K Arabic tweets
14	Mahmoudi et al.	2024	Accuracy of Sentiment Packages in R & Python	Tool comparison, time complexity analysis	Performance varies by dataset	Practical implementation insight	Overfitting on familiar datasets	Seven sentiment datasets
15	Wang et al.	2024	Dual-Perspective Fusion Network	Multimodal GCN, global-local fusion	Outperformed multimodal baselines	Uses fine-grained multimodal cues	Image-text misalignment risk	Twitter multimodal datasets
16	Zhao et al.	2024	Survey on Multimodal ABSA	Systematic survey	Identified trends & gaps	First dedicated MABSA survey	No experiments	Multimodal ABSA datasets
17	Ruan et al.	2024	CECCN for Image Sentiment Analysis	CNN + color correlation + attention	Superior image sentiment accuracy	Considers color psychology	Image-only focus	Image sentiment benchmarks
18	Razali et al.	2024	Hybrid Sentiment Analysis for Gastronomy Tourism	Lexicon + ML + augmentation + BI	Accuracy 0.98, F1 0.99	Handles minority sentiments well	Domain-specific solution	Gastronomy tourism reviews

3. Research Gap

Across the reviewed studies, several clear research gaps remain. Although many works improve sentiment performance by combining lexicons with deep learning or designing context-aware ABSA models, most solutions are still domain- and language-dependent, limiting transferability across platforms, topics, and low-resource languages [1], [4], [5]. Cross-domain robustness continues to be unresolved—systematic reviews emphasize that no single approach consistently performs well across domains because datasets, annotation schemes, and sentiment expressions vary widely [9], and package-level evaluations confirm strong dataset sensitivity and overfitting in practical sentiment tools [14]. While multilingual ABSA and transfer-learning models attempt broader generalization, they often require large, labeled source domains and higher computational cost, which can constrain real-world deployment [4], [6]. In addition, implicit sentiment and context-dependent polarity remain challenging despite recent progress using prototype-guided models and contrastive learning [12]. Multimodal sentiment methods also show promise but still face modality alignment and noise issues when images are weakly related to text, and evaluations remain inconsistent due to limited standardized multimodal benchmarks [15], [16]. Finally, several studies still highlight fundamental gaps in resources, especially annotated corpora and aspect-level datasets for under-resourced languages—restricting reproducibility and fair comparison across methods [1], [13].

4. Systematic result analysis

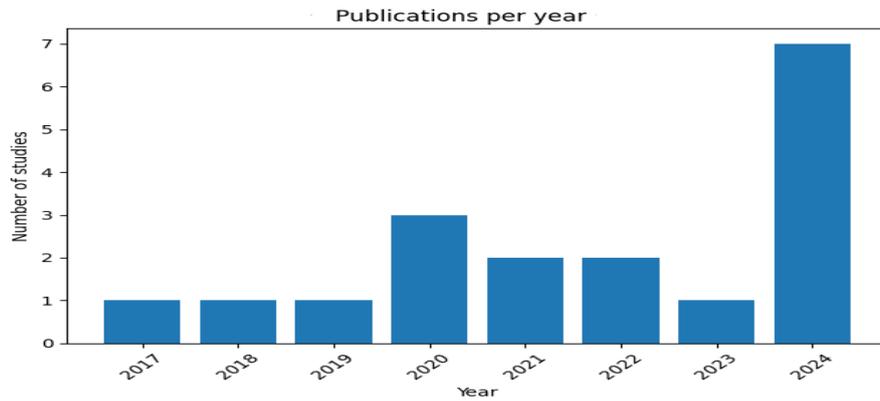


Figure 1: Year-wise Distribution of Publications

Figure 1 illustrates the annual distribution of the reviewed studies. The figure shows a noticeable increase in publications in recent years, indicating the growing research interest in sentiment analysis, particularly in advanced areas such as aspect-based, multilingual, and multimodal sentiment analysis. This trend reflects the rapid evolution of methodologies and the increasing availability of large-scale data.

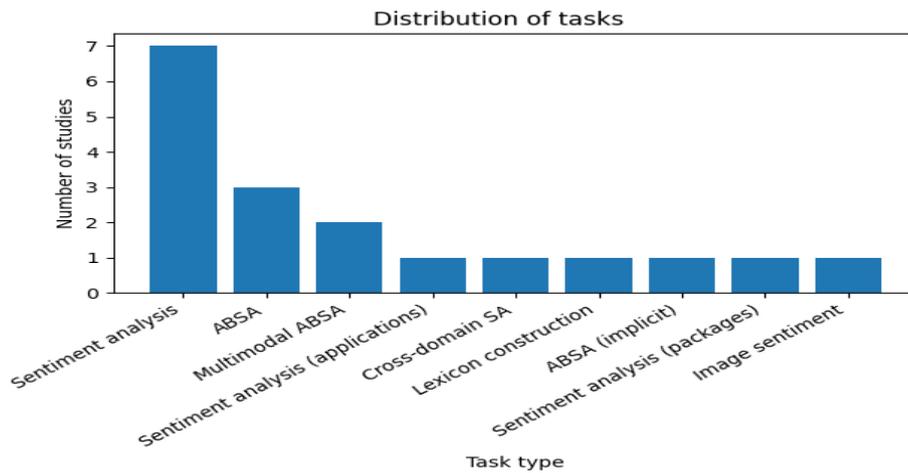


Figure 2: Distribution of Sentiment Analysis Tasks

Figure 2 depicts the proportion of different sentiment analysis tasks addressed by the reviewed studies, including general sentiment analysis, aspect-based sentiment analysis (ABSA), multimodal sentiment analysis, lexicon construction, and survey-based research. The dominance of ABSA-related studies highlights the shift from coarse-grained sentiment classification toward fine-grained, aspect-level analysis.

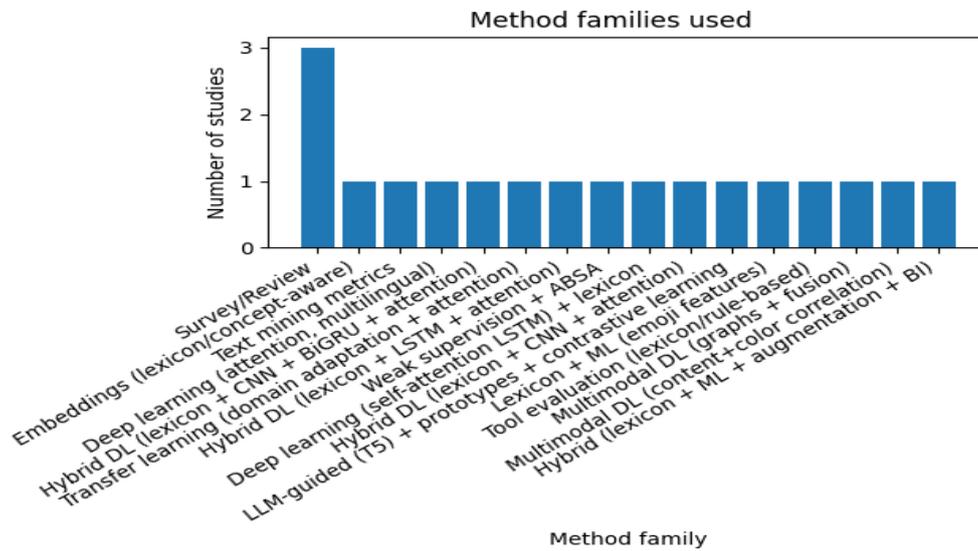


Figure 3: Methodological Approaches Used

Figure 3 categorizes the studies based on the primary methodological approaches employed. The chart shows a strong emphasis on hybrid models that combine sentiment lexicons with deep learning architectures, followed by transfer learning and graph-based methods. Traditional machine learning and purely lexicon-based approaches appear less frequently, indicating a transition toward more context-aware and representation-rich models.

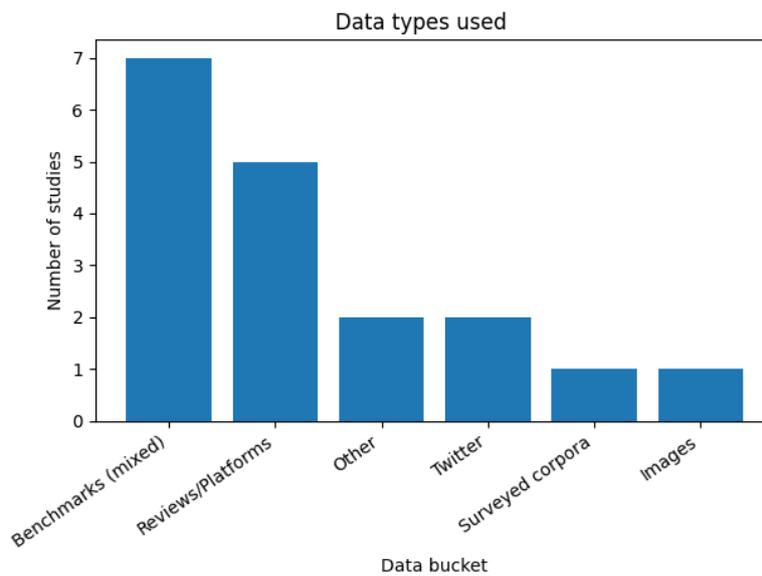


Figure 4: Types of Data Used

Figure 4 summarizes the types of datasets used across the studies, such as social media text (e.g., Twitter), online reviews, benchmark datasets, and multimodal data (text and images). The figure reveals that textual social media and review datasets remain the most common, while multimodal and low-resource language datasets are still relatively limited, highlighting opportunities for future research.

Table 2: Summary of Reviewed Sentiment Analysis Studies (Refs. 1–18)

Ref	Author	Year	Title	MethodType	Task	DataUsed	Data-Bucket
1	Wang et al.	2021	Refined Global Word Embeddings Based on Sentiment Concept	Embeddings (lexicon/concept-aware)	Sentiment analysis	Multiple benchmark datasets	Benchmarks (mixed)
2	Kim	2021	Using Online Reviews for Customer Sentiment Analysis	Text mining metrics	Sentiment analysis	Online reviews	Reviews/PI atforms
3	Smetanin	2020	Applications of Sentiment Analysis for Russian Texts	Survey/Review	Sentiment analysis (applications)	Russian datasets (surveyed)	Benchmarks (mixed)
4	He et al.	2022	LGCF Multilingual Model for ABSA	Deep learning (attention, multilingual)	ABSA	Chinese + English benchmarks	Benchmarks (mixed)
5	Yang et al.	2020	Sentiment Analysis for E-Commerce Reviews in Chinese (SLCABG)	Hybrid DL (lexicon + CNN + BiGRU + attention)	Sentiment analysis	Dangdang book reviews	Reviews/PI atforms
6	Zhang et al.	2023	EATN Adaptive Transfer Network for Aspect-Level SA	Transfer learning (domain adaptation + attention)	ABSA	Six public datasets	Benchmarks (mixed)
7	Fu et al.	2018	Lexicon-Enhanced LSTM with Attention	Hybrid DL (lexicon + LSTM + attention)	Sentiment analysis	English + Chinese datasets	Benchmarks (mixed)
8	Kastrati et al.	2020	Weakly Supervised ABSA on MOOCs Reviews	Weak supervision + ABSA	ABSA	Coursera (~105k) + classroom dataset	Reviews/PI atforms
9	Al-Moslimi et al.	2017	Cross-Domain Sentiment Analysis: SLR	Survey/Review	Cross-domain SA	Studies 2010–2016	Surveyed corpora
10	Deng et al.	2019	Sparse Self-Attention LSTM for Sentiment Lexicon Construction	Deep learning (self-attention LSTM) + lexicon	Lexicon construction	SemEval 2013–2016	Other
11	Huang et al.	2022	SentiCNN (lexicon-based attention CNN)	Hybrid DL (lexicon + CNN + attention)	Sentiment analysis	Two benchmark datasets	Benchmarks (mixed)
12	Su et al.	2024	Prototype Learning + Demonstration for ABSA	LLM-guided (T5) + prototypes + contrastive learning	ABSA (implicit)	Laptop + Restaurant	Other
13	Alfreihat et al.	2024	Emo-SL Emoji Sentiment Lexicon for Arabic Tweets	Lexicon + ML (emoji features)	Sentiment analysis	Arabic tweets (58K)	Twitter
14	Mahmoudi et al.	2024	Lexicon & Rule-Based Packages in R/Python	Tool evaluation (lexicon/rule-based)	Sentiment analysis (packages)	Seven datasets	Benchmarks (mixed)
15	Wang et al.	2024	Dual-Perspective Fusion Network for ABMSA	Multimodal DL (graphs + fusion)	Multimodal ABSA	Two Twitter multimodal datasets	Twitter

16	Zhao et al.	2024	Survey on Multimodal ABSA	Survey/Review	Multimodal ABSA	Corpora reviewed	Re-views/Pl atforms
17	Ruan et al.	2024	CECCN for Image Sentiment Analysis	Multimodal DL (content+color correlation)	Image sentiment	Two image benchmarks	Images
18	Razali et al.	2024	Hybrid SA for Gastronomy Tourism (minority class)	Hybrid (lexicon + ML + augmentation + BI)	Sentiment analysis	Gastronomy tourism reviews	Re-views/Pl atforms

Table 2 presents a structured overview of the selected sentiment analysis and aspect-based sentiment analysis studies. It summarizes each work using key attributes including reference number, first author, publication year, title, employed methods, reported results, main advantages, limitations, and data used. This tabular representation enables a systematic comparison of traditional lexicon-based methods, machine learning models, deep learning approaches, transfer learning, and multimodal techniques. It also highlights the diversity of datasets, ranging from benchmark corpora and social media texts to multilingual and multimodal sources.

5. Conclusion

This comprehensive review examined the evolution of sentiment analysis and aspect-based sentiment analysis, highlighting key methodologies, data sources, and prevailing challenges. Traditional lexicon-based and machine learning approaches laid the foundation for sentiment classification but were constrained by domain dependence and limited contextual understanding. The introduction of deep learning and transformer-based models significantly improved performance by capturing semantic and contextual nuances, while hybrid and multimodal approaches further enhanced sentiment representation. However, despite these advancements, critical challenges remain unresolved, including the scarcity of high-quality annotated datasets for low-resource languages, difficulties in detecting implicit and context-dependent sentiments, limited cross-domain adaptability, and insufficient model interpretability. Furthermore, many existing models struggle to integrate diverse data modalities effectively. Addressing these issues is essential for the development of scalable and reliable sentiment analysis systems capable of real-world deployment. Future research should focus on developing domain-adaptive, explainable, and multimodal sentiment analysis frameworks that can effectively handle implicit opinions and low-resource language scenarios using minimal supervision.

References

1. Y. Wang, G. Huang, J. Li, H. Li, Y. Zhou and H. Jiang, "Refined Global Word Embeddings Based on Sentiment Concept for Sentiment Analysis," in *IEEE Access*, vol. 9, pp. 37075-37085, 2021
2. R. Y. Kim, "Using Online Reviews for Customer Sentiment Analysis," in *IEEE Engineering Management Review*, vol. 49, no. 4, pp. 162-168, 1 Fourthquarter, Dec. 2021
3. S. Smetanin, "The Applications of Sentiment Analysis for Russian Language Texts: Current Challenges and Future Perspectives," in *IEEE Access*, vol. 8, pp. 110693-110719, 2020
4. J. He, A. Wumaier, Z. Kadeer, W. Sun, X. Xin and L. Zheng, "A Local and Global Context Focus Multilingual Learning Model for Aspect-Based Sentiment Analysis," in *IEEE Access*, vol. 10, pp. 84135-84146, 2022
5. L. Yang, Y. Li, J. Wang and R. S. Sherratt, "Sentiment Analysis for E-Commerce Product Reviews in Chinese Based on Sentiment Lexicon and Deep Learning," in *IEEE Access*, vol. 8, pp. 23522-23530, 2020,
6. K. Zhang *et al.*, "EATN: An Efficient Adaptive Transfer Network for Aspect-Level Sentiment Analysis," in *IEEE Transactions on Knowledge and Data Engineering*, vol. 35, no. 1, pp. 377-389, 1 Jan. 2023

7. X. Fu, J. Yang, J. Li, M. Fang and H. Wang, "Lexicon-Enhanced LSTM With Attention for General Sentiment Analysis," in *IEEE Access*, vol. 6, pp. 71884-71891, 2018
8. Z. Kastrati, A. S. Imran and A. Kurti, "Weakly Supervised Framework for Aspect-Based Sentiment Analysis on Students' Reviews of MOOCs," in *IEEE Access*, vol. 8, pp. 106799-106810, 2020
9. T. Al-Moslmi, N. Omar, S. Abdullah and M. Albared, "Approaches to Cross-Domain Sentiment Analysis: A Systematic Literature Review," in *IEEE Access*, vol. 5, pp. 16173-16192, 2017
10. D. Deng, L. Jing, J. Yu and S. Sun, "Sparse Self-Attention LSTM for Sentiment Lexicon Construction," in *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, vol. 27, no. 11, pp. 1777-1790, Nov. 2019
11. M. Huang, H. Xie, Y. Rao, Y. Liu, L. K. M. Poon and F. L. Wang, "Lexicon-Based Sentiment Convolutional Neural Networks for Online Review Analysis," in *IEEE Transactions on Affective Computing*, vol. 13, no. 3, pp. 1337-1348, 1 July-Sept. 2022.
12. H. Su, X. Wang, J. Li, S. Xie and X. Luo, "Enhanced Implicit Sentiment Understanding With Prototype Learning and Demonstration for Aspect-Based Sentiment Analysis," in *IEEE Transactions on Computational Social Systems*, vol. 11, no. 5, pp. 5631-5646, Oct. 2024
13. M. Alfreihat, O. S. Almousa, Y. Tashtoush, A. AlSobeh, K. Mansour and H. Migdady, "Emo-SL Framework: Emoji Sentiment Lexicon Using Text-Based Features and Machine Learning for Sentiment Analysis," in *IEEE Access*, vol. 12, pp. 81793-81812, 2024
14. A. Mahmoudi, D. Jemielniak and L. Ciechanowski, "Assessing Accuracy: A Study of Lexicon and Rule-Based Packages in R and Python for Sentiment Analysis," in *IEEE Access*, vol. 12, pp. 20169-20180, 2024
15. D. Wang, C. Tian, X. Liang, L. Zhao, L. He and Q. Wang, "Dual-Perspective Fusion Network for Aspect-Based Multimodal Sentiment Analysis," in *IEEE Transactions on Multimedia*, vol. 26, pp. 4028-4038, 2024
16. H. Zhao, M. Yang, X. Bai and H. Liu, "A Survey on Multimodal Aspect-Based Sentiment Analysis," in *IEEE Access*, vol. 12, pp. 12039-12052, 2024,
17. S. Ruan, K. Zhang, L. Wu, T. Xu, Q. Liu and E. Chen, "Color Enhanced Cross Correlation Net for Image Sentiment Analysis," in *IEEE Transactions on Multimedia*, vol. 26, pp. 4097-4109, 2024
18. M. N. Razali, S. A. Manaf, R. B. Hanapi, M. R. Salji, L. W. Chiat and K. Nisar, "Enhancing Minority Sentiment Classification in Gastronomy Tourism: A Hybrid Sentiment Analysis Framework With Data Augmentation, Feature Engineering and Business Intelligence," in *IEEE Access*, vol. 12, pp. 49387-49407, 2024