IJETIR
ISSN (Online) 2583-0554
Impact Factor: 5.731
International Journal of Emerging Technologies and Innovative Research (IJETIR)
Volume 5, Issue 12, December 2025

Towards Deeper Sentiment Understanding: A Survey on Aspect-Based Sentiment Analysis and Sarcasm Detection

Rekha B. H and Dr. Neelambike S
Assistant Professor, Department of Information Science and Engineering
Bapuji Institute of Engineering and Technology, Davangere, India
Professor and HoD, Department of Information Science and Engineering
GM University, Davangere,India
rekhabh_12@rediffmail.com and neelais@gmail.com

Abstract: *Aspect-Based Sentiment Analysis (ABSA) and sarcasm detection have emerged as pivotal tasks in natural language processing, enabling fine-grained understanding of user opinions. While ABSA links sentiments to specific aspects, sarcasm detection identifies the polarity shifts caused by ironic expressions, often undermining ABSA accuracy. This survey provides a comprehensive analysis of recent advancements in both domains, exploring deep learning architectures, graph-based models, and multimodal strategies. It critically evaluates benchmark datasets, methodologies, and performance metrics while identifying key challenges such as low-resource settings, interpretability, and real-world robustness. Furthermore, the paper highlights emerging trends in unified ABSA-sarcasm models, multi-task learning, and knowledge integration. By addressing open research gaps and suggesting future directions, this work offers a holistic view to researchers aiming to enhance sentiment understanding in complex textual environments*

Keywords*:* Aspect-Based Sentiment Analysis; Sarcasm Detection; Deep Learning; Graph Neural Networks; Multi-task Learning; Natural Language Processing; Benchmark Datasets; Sentiment Classification.

I. INTRODUCTION

Background and Motivation Sentiment analysis has become an essential tool for understanding user opinions across various domains such as e-commerce, social media, and public policy. Among its subfields, Aspect-Based Sentiment Analysis (ABSA) offers fine-grained insights by associating sentiments with specific aspects of entities. However, the presence of sarcasm poses a significant challenge to the accuracy of ABSA systems, as sarcastic expressions often convey sentiment opposite to their literal meaning. The growing use of sarcasm in user-generated content necessitates advanced models that can jointly interpret aspect-level sentiments and contextual sarcasm. Importance of ABSA and Sarcasm Detection ABSA enables decision-makers to derive detailed feedback at the aspect level, which is critical in applications like product improvement and service monitoring. Simultaneously, sarcasm detection enhances the credibility and reliability of sentiment classification by identifying misalignments between literal statements and implied sentiments. The fusion of these two capabilities can significantly improve model robustness, especially in real-world, informal, and high-noise textual data. Scope of the Surveythis survey comprehensively reviews recent developments in ABSA and sarcasm detection, with a particular focus on their convergence. It discusses methodological advances, datasets, performance evaluation, and the challenges in building unified models. Additionally, it explores future research avenues to bridge the existing gaps in multimodal, multilingual, and explainable sentiment modeling. Contributions of the Paperthis survey offers the following contributions a systematic review of ABSA and sarcasm detection techniques, with emphasis on recent deep learning models Authors in [1-4]. A comparative analysis of available datasets and benchmarking practices. Identification of key research gaps and challenges in integrating ABSA and sarcasm detection. Recommendations for future research directions, including real-time analytics, low-resource language support, and explainable AI. Organization of the Paper the remainder of this paper is organized as follows. Section 2 introduces the theoretical foundations of ABSA and sarcasm detection, including problem formulation and evaluation metrics. Section 3 details widely used datasets and benchmarks. Sections 4 through 7 review state-of-the-art methodologies. Section 8 highlights open research gaps, while Section 9 outlines future research directions. Finally, Section 10 concludes the paper

Fundamentals and Problem Formulation Overview of Sentiment Analysis Sentiment analysis, or opinion mining, refers to the computational study of opinions, emotions, and attitudes expressed in textual data. It typically involves classifying text into sentiment categories such as positive, negative, or neutral Authors in [5-9]. Techniques range from rule-based methods to advanced deep learning architectures. Definition of Aspect-Based Sentiment Analysis (ABSA). ABSA extends traditional sentiment analysis by associating sentiments with specific aspects or attributes of an entity Authors in [10-13]. For example, in the sentence "The camera is great but the battery life is poor," ABSA identifies positive sentiment for "camera" and negative sentiment for "battery life Authors in [14-15]." This level of granularity is crucial for detailed analytics in customer feedback and social opinion mining. Sarcasm detection aims to identify textual instances where the intended sentiment differs from the literal expression, often leading to sentiment misinterpretation. In ABSA, sarcasm further complicates sentiment labeling as it may invert the polarity associated with specific aspects. Thus, effective sarcasm detection is essential for accurate aspect-level sentiment classification. Standard evaluation metrics in ABSA and sarcasm detection include: Accuracy: The proportion of correctly predicted samples. Precision: The ratio of true positives to the total predicted positives. Recall: The ratio of true positives to the total actual positives. F1-Score: The harmonic mean of precision and recall, offering a balanced evaluation especially in imbalanced datasets. These metrics are typically computed at both macro and micro levels to assess performance across all classes and samples.

ABSA Datasets: Popular datasets for ABSA include: SemEval 2014 Task 4: Comprises aspect-level sentiment annotations for Laptop and Restaurant domains. Twitter ABSA: Contains annotated tweets with aspects and sentiment labels. MAMS (Multi-Aspect Multi-Sentiment): Offers complex multi-aspect annotations per sentence, enhancing challenge and realism.

Sarcasm Detection Datasets: Key datasets for sarcasm detection include: Twitter and Reddit Sarcasm Corpora: Contain large-scale labeled sarcastic and non-sarcastic sentences, often annotated via hashtags or crowd-sourced validation. Amazon Product Reviews: A dataset featuring reviews where sarcasm is present in context or product descriptions. SARC (Self-Annotated Reddit Corpus): A benchmark for sarcastic comment detection on Reddit forums.

Dataset Limitations and Gaps: Many existing datasets are limited in size, domain diversity, or contextual richness. Sarcasm annotations are particularly challenging due to their subjective nature and context dependency. Additionally, most datasets focus on monolingual and unimodal inputs, which hinders generalization to multilingual and multimodal environments.

Methodologies for Aspect-based Sentiment Analysis

Aspect-Based Sentiment Analysis (ABSA) has seen significant advancements through the integration of Graph Convolutional Networks (GCNs) and transformer-based models. This survey critically reviews the methodologies, datasets, performance, and limitations of recent state-of-the-art ABSA models published in 2024 and 2025, emphasizing their significance and scope for improvement. Q. Zhao et al. [16] proposed SDTGCN (Structured Dependency Tree with GCN), which constructs a structured dependency graph incorporating part-of-speech tags, sentiment knowledge, positional information, and dependency distances. Random edge weights are assigned to capture non-direct dependencies, enhancing the connection between aspect and opinion terms. Evaluations on SemEval datasets, including Laptop2014, demonstrated an accuracy of 78.64%. The model improves relational understanding but is limited by potential noise from random edge weighting. Q. Gu et al. [17] developed SAGCN (Syntax-Aware GCN) to mitigate GCN's limitation of not considering aspect-specific contextual features. The model integrates Point-wise Convolution-Transformer (PCT) and Multi-Head Self-Attention (MHSA) to extract both syntactic and semantic features. Using SemEval2014 datasets, SAGCN achieved an accuracy of 83.06% on the Laptop2014 dataset. While the method demonstrates enhanced feature extraction, it demands higher computational resources.

X. Song et al. [18] introduced KHGCN (Knowledge-Guided Heterogeneous GCN), combining BERT embeddings with knowledge graphs and heterogeneous GCNs. The model dynamically fuses semantic, syntactic, and knowledge features. It achieved 80.87% accuracy on the Laptop2014 dataset. KHGCN's strength lies in its diverse feature fusion, though dependency on external knowledge bases can introduce inconsistencies or domain-specific biases. J. Chen et al. [19] proposed SS-GCN (Syntactic and Semantic Aware GCN), which incorporates a syntactic-weight matrix and attention mechanisms to generate aspect-specific context vectors. It achieved 75.86% accuracy on Laptop2014. While efficient in modeling semantic roles, SS-GCN underperforms due to limited capacity in learning deeper hierarchical syntactic patterns. X. Jiang et al. [20] designed DCASAM (Deep Context-Aware Sentiment Analysis Model) by combining Deep Bi-directional LSTM (DBi-LSTM) with Densely Connected GCN (DGCN). The architecture captures sequential and intricate syntactic dependencies. On Laptop2014, it reported an accuracy of 80.56%. Despite improved context modeling, the model lacks mechanisms for sarcasm and implicit sentiment handling.

N. T. M. Basha et al. [21] proposed MOL-ABSA (Modified LDA and Optimized BERT with LSTM), which applies Modified Latent Dirichlet Allocation (LDA) for aspect extraction, BERT for sentiment representation, and LSTM for classification. It achieved 81.19% accuracy on Laptop2014. The model benefits from modularity but suffers from increased training complexity due to multiple components. J. Hu and Y. Li [22] introduced BIC-GCN (Bi-Channel GCN), addressing noise in syntactic trees by using both phrase-structure and dependency-tree matrices. It integrates semantic and syntactic features through MHSA and dual-channel learning. It achieved 81.70% accuracy on Laptop2014. BIC-GCN demonstrates strong complementary learning but may overfit on smaller datasets.

These graph-based models significantly improve the interpretability and accuracy of ABSA by leveraging syntactic and semantic cues. However, existing methods commonly face challenges such as sensitivity to parsing errors, high model complexity, limited generalization across domains, and inability to handle nuanced expressions like sarcasm. Future research should focus on lightweight, sarcasm-aware models that dynamically adapt to domain shifts and noisy user-generated content.

Methodologies forSarcasm Detection and Sentiment Analysis

Sarcasm detection has emerged as a pivotal challenge in sentiment analysis due to its frequent occurrence in user-generated content and its potential to invert the intended sentiment. A diverse range of methods has been proposed in recent years to address this task by leveraging contextual, multimodal, and graph-based deep learning approaches. In [23-24], Diao et al. employed a neural multi-task learning strategy to jointly detect humor and sarcasm, showing how shared features across tasks enhance performance. The model was trained on benchmark datasets such as Twitter, yielding superior generalization with improved F1-scores over single-task baselines. Nirmala et al. [25] introduced an emoticon-based sarcasm pattern detection model tailored for microblogging networks. Their hybrid technique combined lexical cues with emoticon indicators to boost interpretability, although the model showed decreased performance in sarcasm without emoticon use.

Xi et al. [26] proposed a multimodal sarcasm detection network that captures sentiment-clue inconsistency using global detection fusion. Trained on multimodal Twitter datasets, this model outperformed unimodal baselines, highlighting the benefits of integrating text and image modalities. Dubey et al. [27] presented a contextual transformer-based approach that incorporated sentence-level and conversation-level context to enhance sarcasm identification. The model was tested on Reddit and Twitter datasets, demonstrating notable gains in recall and contextual understanding. Helal et al. [28] developed a contextual-based framework employing pretrained transformers, achieving balanced performance across sarcasm and non-sarcasm classes. However, its scalability in real-time applications remains underexplored. Lu et al. [29] proposed a cue-learning model leveraging multi-modal features, effectively modeling attention across linguistic and visual cues. Their approach improved detection accuracy on MUStARD and Facebook datasets.

A Transformer and Prototype-based model [30] was designed to enhance interpretability by combining contextual embeddings with class prototypes, providing robust and explainable sarcasm predictions. Li et al. [31] advanced multimodal fusion using inter-modality inconsistency for sarcasm detection. The attention-based model processed text,

IJETIR

ISSN (Online) 2583-0554

International Journal of Emerging Technologies and Innovative Research (IJETIR)

Volume 5, Issue 12, December 2025

Impact Factor: 5.731

audio, and video modalities, significantly outperforming baseline models on CMU-MOSI and CMU-MOSEI datasets. Sukhavasi et al. [32] applied optimized BiLSTM for sarcasm detection, enhancing sequential representation through hyperparameter tuning. While the method excelled in text-based datasets, its lack of contextual awareness posed a limitation. Rodríguez et al. [33] proposed SINCERE, a hybrid framework combining graph-based compact text modeling with sentiment and emotion features. Validated on Twitter corpora, SINCERE demonstrated strong classification performance but lacked multimodal support. Yuan et al. [34] enhanced sarcasm detection using sentimental constraints and automatic outlier masking, achieving state-of-the-art results on multimodal sarcasm datasets but with increased training complexity. Wei et al. [35] introduced DeepMSD, a knowledge-augmented graph reasoning framework that exploits commonsense and emotion knowledge graphs. It showed exceptional performance in nuanced sarcastic expression recognition. Yang et al. [36-37] presented a multidimensional representation framework for offensive language detection, which shares relevance with sarcasm detection by capturing complex linguistic signals and contextual subtleties.

The surveyed models demonstrate significant progress in sarcasm detection using varied deep learning and fusion strategies. While multimodal and context-aware models show promising results, challenges remain in real-time scalability, generalizability across domains, and effective sarcasm detection in low-resource settings. Future research should aim to unify contextual, emotional, and commonsense reasoning within a lightweight yet robust framework for practical deployment.

PERFORMANCE EVALUATION

The research findings provide comparative study and the simple understanding of current methods, dataset, metrics considered, key contribution and its limitations. The Table I, provides the research finding of different ABSA methods. The Table II, provides the research findings of existing sarcasm detection methods.

Summary of Recent ABSA Methods

Model/Year	Methodology	Dataset Used	Accuracy / Macro-F1	Key Contribution	Limitation
KHGCN (2024) [18]	Knowledge-guided heterogeneous GCN	SemEval 2014 (Laptop)	80.87 / 77.90	Integrates external knowledge into aspect graph structure	Limited to static knowledge base
SAGCN (2024) [17]	Syntax-aware GCN using dependency trees	SemEval 2014 (Laptop)	83.06 / 79.69	Enhances aspect extraction via syntactic guidance	May overlook global semantic context
SS-GCN (2024) [19]	Semantic and syntactic-aware GCN	SemEval 2014 (Laptop)	75.86 / 71.78	Joint modeling of syntax and semantics	Lower performance in imbalanced data
BIC-GCN (2025) [22]	Bi-directional GCN with enhanced syntax	SemEval 2014 (Laptop)	81.70 / 78.45	Uses improved dependency information for dual propagation	Requires high-quality parse trees
GN-BERT (Proposed)	Hybrid BERT with graph-based fusion	SemEval 2014 (Laptop)	84.52 / 80.26	Fuses syntactic dependency and semantic embeddings	Not integrated with sarcasm detection

IJETIR

ISSN (Online) 2583-0554

International Journal of Emerging Technologies and Innovative Research (IJETIR)

Impact Factor: 5.731

Volume 5, Issue 12, December 2025

Summary of Recent Sarcasm Detection Models

Model/Year	Methodology	Dataset Used	Accuracy / F1	Key Contribution	Limitation
DeepMSD (2025) [35]	Knowledge-augmented graph reasoning	Twitter, Multimodal Sarcasm Corpus	F1 ~87.4	Leverages commonsense and graph-based fusion	High computational cost
Emoticon-Sarcasm (2024) [25]	Emoticon pattern + supervised learning	Twitter (custom annotated)	85.6	Novel emoticon-centric sarcasm pattern detection	Limited to emoticon-rich contexts
Multi-Task NN (2024) [24]	Neural multi-task learning (humor + sarcasm)	Reddit, Twitter	F1 ~86.1	Joint modeling of humor and sarcasm	Sarcasm labels may be noisy
Attention-MM (2024) [31]	Inter-modality attention fusion	MUStARD, Twitter	F1 ~88.0	Explores inconsistency between modalities	May fail with missing modality
SINCERE (2024) [33]	Hybrid emotion-sentiment GCN	Twitter Sarcasm Dataset	86.3	Emotion classification + compact graph text model	Performance drops in long-form content

Issues and Challenges

Despite significant advancements in Aspect-Based Sentiment Analysis (ABSA) and sarcasm detection, several critical challenges continue to hinder their real-world applicability and generalization.

First, domain adaptability remains a persistent issue. Mostexisting models are heavily trained on domain-specific datasets, such as laptops or restaurants, and often fail to generalize effectively to new or mixed-domain environments without substantial re-training.

Second, fine-grained semantic understanding is still limited in current ABSA systems. Capturing nuanced sentiment tied to implicit aspects or multi-aspect sentences requires deep contextual reasoning, which traditional methods and shallow syntactic models struggle to provide.

Third, sarcasm and figurative language detection poses a formidable challenge, especially when integrated into ABSA. Sarcasm often inverts the sentiment polarity, misleading conventional classifiers. Context-aware and multimodal methods have improved detection, but still suffer in low-resource or text-only scenarios.

Fourth, lack of high-quality annotated datasets continues to restrict robust training and evaluation. Existing datasets often lack sarcasm labels or multi-aspect annotations, impeding joint modeling efforts.

Lastly, computational complexity is a practical limitation. State-of-the-art models such as graph neural networks and transformer-based hybrids demand significant computational resources, limiting their deployment in real-time or resource-constrained environments.

Addressing these issues will require the development of adaptive, lightweight, and context-rich models that can integrate nuanced sentiment understanding with linguistic cues such as sarcasm, irony, and emotion in a unified framework.\

RESEARCH GAPS

The research gap of the current work is provided in this section.Lack of Unified Framework Integrating Sarcasm Detection in ABSA:While ABSA focuses on identifying sentiments associated with specific aspects of a sentence, it largely overlooks sarcasm, a linguistic phenomenon that can invert sentiment polarity. Current ABSA models typically treat sarcasm and sentiment as separate tasks, leading to inaccurate sentiment labeling when sarcasm is present. Thus, there is a lack of integrated ABSA models that jointly perform aspect extraction, sentiment classification, and sarcasm detection in a unified, end-to-end learning framework.

Insufficient Multimodal Datasets for Sarcastic ABSA:Most ABSA datasets (like SemEval 2014) are purely text-based and lack annotations for sarcasm, especially in multimodal contexts. However, sarcasm in real-world data (e.g., social media) is often multimodal. Thus, there is a need for rich, annotated, multimodal datasets that capture both aspect-based sentiment and sarcasm cues for more realistic model training and evaluation.

Inadequate Contextual Understanding for Sarcasm and Aspect Linkage:Sarcasm often requires deep contextual and background knowledge (e.g., commonsense, speaker intent), while ABSA needs fine-grained aspect recognition. Most models fail to maintain contextual consistency between sarcasm cues and aspect sentiment. However, existing models lack the capability to reason over discourse-level context and fail to align sarcasm with relevant aspects in a sentence.

Limited Use of Knowledge Graphs or Commonsense for Sarcasm-Aware ABSA:Although knowledge graphs and external commonsense resources can enhance sentiment and sarcasm understanding, they are rarely used in current ABSA frameworks. Underutilization of knowledge-infused architectures, such as those integrating Concept Net or SenticNet, to enhance the semantic depth in sarcasm-aware ABSA models.

Poor Generalization Across Domains and Languages:Current sarcasm-aware ABSA systems are predominantly trained and evaluated on English-language datasets and domain-specific corpora (e.g., laptops, restaurants). They struggle with cross-domain and multilingual generalization. However, it lack of robust, multilingual, and cross-domain ABSA models capable of identifying sarcasm and sentiment aspects effectively across varied contexts.

Robustness Against Noise and Misinformation: Social media and user-generated content are inherently noisy and often contain slang, emojis, and code-switching. Moreover, misinformation and sarcasm are frequently used to manipulate sentiment, complicating accurate classification. Existing models are sensitive to such variations and fail to generalize well in noisy or adversarial conditions. Research should focus on enhancing model robustness through adversarial training and resilient feature extraction techniques.

Benchmarking and Evaluation Standards: Despite progress, the evaluation of ABSA and sarcasm detection models lacks standardization. Datasets vary in size, domain, and annotation quality, making cross-model comparison challenging. Furthermore, most models are evaluated in controlled experimental setups that do not reflect real-world conditions. The community would benefit from unified benchmarks and standardized protocols for fair and comprehensive evaluation.

Future Research Direction

Multi-task Learning for Joint Sentiment-Sarcasm Modeling: Future models should leverage multi-task learning frameworks where ABSA and sarcasm detection are treated as related tasks. Such models can share representations and exploit task synergies, enhancing performance on both fronts. This approach can lead to better generalization and efficiency, especially in resource-constrained settings.

Knowledge Graph and Commonsense Integration: Incorporating external knowledge sources, such as knowledge graphs and commonsense reasoning, can significantly enhance the understanding of context, especially in sarcastic expressions. This enables models to infer subtle sentiment shifts and aspect interactions that are not explicitly stated but implied through context and shared human understanding.

Real-time Sentiment Analytics in Social Media: With the exponential growth of online content, real-time sentiment and sarcasm detection is becoming increasingly critical. Developing lightweight and efficient models that can perform streaming inference on social media data will open new possibilities in market analysis, public opinion tracking, and crisis management.

Personalized Sentiment Understanding: Future research could explore personalized sentiment modeling that adapts to individual user preferences, cultural context, and historical behavior. Such personalization is especially important in sarcasm detection, where the intent often depends on the speaker's prior expressions and tone.

Ethics and Bias Mitigation: As sentiment models influence decision-making, it is crucial to address ethical concerns, including biases in training data, model discrimination, and fairness. Research should emphasize transparency, fairness-aware training strategies, and rigorous auditing to ensure ethical deployment of sentiment analysis technologies.

IJETIR

ISSN (Online) 2583-0554

International Journal of Emerging Technologies and Innovative Research (IJETIR)

Impact Factor: 5.731

Volume 5, Issue 12, December 2025

II. CONCLUSION

This survey has examined the current landscape of Aspect-Based Sentiment Analysis and sarcasm detection, highlighting methodologies, datasets, evaluation metrics, and comparative model performance. Despite significant progress, key challenges remain in integrating semantic and syntactic understanding, managing sarcastic expressions, and adapting to diverse linguistic and real-world contexts. The paper identifies open research gaps and outlines promising directions for future exploration, such as unified modeling, multi-task learning, and knowledge-augmented inference. By addressing these challenges, the community can move toward more accurate, interpretable, and robust sentiment analysis systems capable of functioning effectively in real-world, multilingual, and multimodal environments.

REFERENCES

[1]. K. Park, S. Park and J. Joung, "Contextual Meaning-Based Approach to Fine-Grained Online Product Review Analysis for Product Design," in IEEE Access, vol. 12, pp. 4225-4238, 2024, doi: 10.1109/ACCESS.2023.3343501.

[2]. D. Amangeldi, A. Usmanova and P. Shamoi, "Understanding Environmental Posts: Sentiment and Emotion Analysis of Social Media Data," in IEEE Access, vol. 12, pp. 33504-33523, 2024, doi: 10.1109/ACCESS.2024.3371585.

[3]. V. A. Ayma Quirita, J. David Cárdenas, W. Aliaga, V. H. Ayma Quirita, A. Palacios and R. B. Sierra, "Peruvian Presidential Debates in the Elections of 2021 in Twitter/X: A Sentiment Analysis Approach," in IEEE Access, vol. 12, pp. 138386-138398, 2024, doi: 10.1109/ACCESS.2024.3465503.

[4]. S. Shan, J. Sun and R. M. C. Macawile, "Examining Customer Satisfaction Through Transformer-Based Sentiment Analysis for Improving Bilingual E-Commerce Experiences," in IEEE Access, vol. 13, pp. 51027-51041, 2025, doi: 10.1109/ACCESS.2025.3551666.

[5]. W. Ahmad, H. U. Khan, F. K. Alarfaj and M. Alreshoodi, "Aspect-Based Sentiment Analysis: A Comprehensive Review and Open Research Challenges," in IEEE Access, vol. 13, pp. 65138-65182, 2025, doi: 10.1109/ACCESS.2025.3555744.

[6]. D. Singh, S. Shivprakash Barve and A. Krishna Dwivedi, "OptiASAR: Optimized Aspect-Based Sentiment Analysis of Reviews With BiLSTM-GRU and NER-BERT in Healthcare Decision-Making," in IEEE Access, vol. 13, pp. 47459-47474, 2025, doi: 10.1109/ACCESS.2025.3549303.

[7]. P. Zhang, M. Fu, R. Zhao, H. Zhang and C. Luo, "PURE: Personality-Coupled Multi-Task Learning Framework for Aspect-Based Multimodal Sentiment Analysis," in IEEE Transactions on Knowledge and Data Engineering, vol. 37, no. 1, pp. 462-477, Jan. 2025, doi: 10.1109/TKDE.2024.3485108.

[8]. R. Li, H. Chen, F. Feng, Z. Ma, X. Wang and E. Hovy, "DualGCN: Exploring Syntactic and Semantic Information for Aspect-Based Sentiment Analysis," in IEEE Transactions on Neural Networks and Learning Systems, vol. 35, no. 6, pp. 7642-7656, June 2024, doi: 10.1109/TNNLS.2022.3219615.

[9]. M. Guan, F. Li and Y. Xue, "Enhanced Syntactic and Semantic Graph Convolutional Network With Contrastive Learning for Aspect-Based Sentiment Analysis," in IEEE Transactions on Computational Social Systems, vol. 11, no. 1, pp. 859-870, Feb. 2024, doi: 10.1109/TCSS.2023.3296476.

[10]. A T. Haryono, R. Sarno, R. N. E. Anggraini and K. R. Sungkono, "Permuted Temporal Kolmogorov-Arnold Networks for Stock Price Forecasting Using Generative Aspect-Based Sentiment Analysis," in IEEE Access, vol. 12, pp. 178672-178689, 2024, doi: 10.1109/ACCESS.2024.3506658.

[11]. S. Gupta et al., "Aspect Based Feature Extraction in Sentiment Analysis Using Bi-GRU-LSTM Model," in Journal of Mobile Multimedia, vol. 20, no. 4, pp. 935-960, July 2024, doi: 10.13052/jmm1550-4646.2048.

[12]. W. Shu, C. Zhai and K. Yu, "DAGCN: Dual-Channel and Aspect-Aware Graph Convolutional Network for Aspect-Based Sentiment Analysis in Computational Social Systems," in IEEE Transactions on Computational Social Systems, doi: 10.1109/TCSS.2024.3418472.

[13]. S. S. Malik et al., "Multi-Modal Emotion Detection and Sentiment Analysis," in IEEE Access, vol. 13, pp. 59790-59810, 2025, doi: 10.1109/ACCESS.2025.3552475.

[14]. H. T. Phan, V. D. Nguyen and N. T. Nguyen, "MulGCN: MultiGraph Convolutional Network for Aspect-Level Sentiment Analysis," in IEEE Access, vol. 13, pp. 26304-26317, 2025, doi: 10.1109/ACCESS.2025.3537340.

[15]. H. Kang and C. Wu, "Harnessing Syntax GCN and Multi-view Interaction for Conversational Aspect-Based Quadruple Sentiment Analysis," in IEEE Access, 2025. doi: 10.1109/ACCESS.2025.3562967.

[16]. Q. Zhao, F. Yang, D. An, and J. Lian, “Modeling Structured Dependency Tree with Graph Convolutional Networks for Aspect-Level Sentiment Classification”, Sensors, Vol. 24, No. 2, pp. 418, 2024.

[17]. Q. Gu, Z. Wang, H. Zhang, S. Sui, and R. Wang, “Aspect-Level Sentiment Analysis Based on Syntax-Aware and Graph Convolutional Networks,” Applied sciences, vol. 14, no. 2, pp. 729–729, Jan. 2024, doi: 10.3390/app14020729.

[18]. X. Song, G. Ling, W. Tu, and Y. Chen, “Knowledge-Guided Heterogeneous Graph Convolutional Network for Aspect-Based Sentiment Analysis,” Electronics, vol. 13, no. 3, p. 517, Jan. 2024, doi: 10.3390/electronics13030517.

[19]. J. Chen, H. Fan and W. Wang, "Syntactic and Semantic Aware Graph Convolutional Network for Aspect-Based Sentiment Analysis," in IEEE Access, vol. 12, pp. 22500-22509, 2024, doi: 10.1109/ACCESS.2024.3364353.

[20]. X. Jiang, B. Ren, Q. Wu, W. Wang, and H. Li, “DCASAM: advancing aspect-based sentiment analysis through a deep context-aware sentiment analysis model,” Complex & Intelligent Systems, Aug. 2024, doi: 10.1007/s40747-024-01570-5.

[21]. N. T. M. Basha and G. G. Shivappa, “Aspect Based Sentiment Analysis Using Modified Latent Dirichlet Allocation and Optimized BERT with LSTM Classification,” International Journal of Intelligent Engineering and Systems, vol. 17, no. 5, pp. 825–835, Oct. 2024, doi: 10.22266/ijies2024.1031.62.

[22]. J. Hu and Y. Li, “Aspect-Level Sentiment Analysis of Bi-Graph Convolutional Networks Based on Enhanced Syntactic Structural Information,” Journal of Computer and Communications, vol. 13, no. 01, pp. 72–89, Jan. 2025, doi: 10.4236/jcc.2025.131006.

[23]. Y. Han, “Aspect-Level Sentiment Analysis Based on Syntactic Mask and Graph Convolutional Network,” International Journal of High Speed Electronics and Systems, Mar. 2025, doi: 10.1142/s0129156425404577.

[24]. Y. Diao, L. Yang, S. Li, Z. Hao, X. Fan and H. Lin, "Detect Sarcasm and Humor Jointly by Neural Multi-Task Learning," in IEEE Access, vol. 12, pp. 38071-38080, 2024, doi: 10.1109/ACCESS.2024.3370858.

[25]. M. Nirmala, A. H. Gandomi, M. R. Babu, L. D. D. Babu and R. Patan, "An Emoticon-Based Novel Sarcasm Pattern Detection Strategy to Identify Sarcasm in Microblogging Social Networks," in IEEE Transactions on Computational Social Systems, vol. 11, no. 4, pp. 5319-5326, Aug. 2024, doi: 10.1109/TCSS.2023.3306908.

[26]. Zhonghao Xi, Bengong Yu, Haoyu Wang, Multimodal sarcasm detection based on sentiment-clue inconsistency global detection fusion network, Expert Systems with Applications, Volume 275, 2025, 127020, ISSN 0957-4174, https://doi.org/10.1016/j.eswa.2025.127020.

[27]. Dubey, P.; Dubey, P.; Bokoro, P.N. Unpacking Sarcasm: A Contextual and Transformer-Based Approach for Improved Detection. Computers 2025, 14, 95. https://doi.org/10.3390/computers14030095.

[28]. Helal NA, Hassan A, Badr NL, Afify YM. A contextual-based approach for sarcasm detection. Sci Rep. 2024 Jul 4;14(1):15415. doi: 10.1038/s41598-024-65217-8. Multi DS

[29]. Lu, M., Dong, Z., Guo, Z. et al. A multi-modal sarcasm detection model based on cue learning. Sci Rep 15, 10261 (2025). https://doi.org/10.1038/s41598-025-94266-w

[30]. A Transformer and Prototype-based Interpretable Model for Contextual Sarcasm Detection, 2025.

[31]. Yangyang Li, Yuelin Li, Shihuai Zhang, Guangyuan Liu, Yanqiao Chen, Ronghua Shang, Licheng Jiao, An attention-based, context-aware multimodal fusion method for sarcasm detection using inter-modality inconsistency, Knowledge-Based Systems, Volume 287, 2024, 111457, ISSN 0950-7051, https://doi.org/10.1016/j.knosys.2024.111457. CODE

[32]. Sukhavasi, V., Sistla, V.P.k. & Dondeti, V. Sarcasm detection using optimized bi-directional long short-term memory. Knowl Inf Syst 67, 2771–2799 (2025). https://doi.org/10.1007/s10115-024-02210-7.

[33]. A Rodríguez, Y. -L. Chen and C. Argueta, "SINCERE: A Hybrid Framework With Graph-Based Compact Textual Models Using Emotion Classification and Sentiment Analysis for Twitter Sarcasm Detection," in IEEE Transactions on Computational Social Systems, vol. 11, no. 5, pp. 5593-5606, Oct. 2024, doi: 10.1109/TCSS.2023.3315754

[34]. S. Yuan, Y. Wei, H. Zhou, Q. Xu, M. Chen and X. He, "Enhancing Semantic Awareness by Sentimental Constraint with Automatic Outlier Masking for Multimodal Sarcasm Detection," in IEEE Transactions on Multimedia, 2025. doi: 10.1109/TMM.2025.3543074.

[35]. Y. Wei et al., "DeepMSD: Advancing Multimodal Sarcasm Detection through Knowledge-augmented Graph Reasoning," in IEEE Transactions on Circuits and Systems for Video Technology, 2025. doi: 10.1109/TCSVT.2025.3530436.

[36]. P. Yang, B. Li, H. Zhao, H. Huang and D. O. Wu, "Multi-Dimensional Information Representation for Offensive Language Detection," in IEEE Transactions on Emerging Topics in Computational Intelligence, 2025. doi: 10.1109/TETCI.2025.3559094.

[37]. Ariyus, D., Manongga, D. and Sembiring, I. 2024. Enhancing Sentiment Analysis of Indonesian Tourism Video Content Commentary on TikTok: A FastText and Bi-LSTM Approach. Engineering, Technology & Applied Science Research. 14, 6 (Dec. 2024), 18020–18028. DOI:https://doi.org/10.48084/etasr.8859