Available online at https://www.gyanvihar.org/researchjournals/ctm_journals.php
SGVU International Journal of Convergence of Technology and Management
E-ISSN: 2455-7528
Vol.10 Issue 2 Page No 18-27

A Comprehensive Review for Sentiment Classification and Analysis with Aspect-Specific Opinion

[1] Srawan Nath, Richa [1] Rawal, [2]Anil Pal
[1]Research Scholar, Computer Science and Engineering, Suresh Gyan Vihar University Jaipur
[2]Associate Professor, Computer Science and Engineering, Suresh Gyan Vihar University Jaipur
Email: nath.srawan@gmail.com

***Abstract**: -* Sentiment analysis has emerged as a prominent industry for gauging public opinion across diverse domains. This paper presents a thorough examination of sentiment analysis focusing on aspect-specific opinions. Aspect-based sentiment analysis involves categorizing sentiments based on specific features or aspects of entities or objects, offering a deeper understanding of user sentiment towards different facets of products, services, or topics. This review encompasses a wide array of methodologies, techniques, and applications related to aspect-specific sentiment analysis. It covers various approaches ranging from traditional lexicon-based methods to advanced techniques employing machine learning and deep learning algorithms, elucidating their strengths, limitations, and comparative effectiveness. Practical applications of aspect-specific sentiment analysis across domains such as product reviews, social media discussions, customer feedback, and market analysis are meticulously examined. Furthermore, emerging trends and challenges in aspect-specific sentiment analysis are discussed, providing valuable insights for researchers. Based on an extensive review of approximately 2500 published papers from various journals and conference proceedings spanning 17 years, this paper serves as a roadmap for future research in sentiment analysis advancements and classifications, particularly concerning aspect-specific.

Keywords: Aspect-specific opinion, Sentiment classification, Advance techniques, Social media

1. Introduction

In recent years, sentiment classification and analysis have witnessed a surge in automated data collection from diverse sources such as marketing, customer feedback analysis, social media monitoring, and market research [1]. While conventional approaches primarily focused on determining the overall sentiment polarity of text, they often overlooked nuanced opinions expressed towards specific aspects or entities within the text, thereby neglecting aspect-specific sentiment mining. However, delving into detailed sentiments towards specific aspects is imperative for gaining profound insights into user preferences, product attributes, and overall sentiment dynamics [2,3]. Previous research has made significant strides in sentiment classification and analysis; nevertheless, a conspicuous research gap exists in the comprehensive exploration and analysis of sentiment classification with aspect-specific opinion mining. Existing literature reviews frequently lack a thorough examination of methodologies, techniques, datasets, and evaluation metrics tailored specifically for aspect-specific sentiment analysis [4-6]. Despite the growing significance of aspect-specific opinion mining across various domains, a comprehensive review paper is needed to synthesize existing research findings, highlight emerging trends, and identify key challenges and opportunities in this domain [7].

There has been a notable shift in focus from numerical analysis to text as a prominent object of research. Natural Language Processing (NLP) has particularly benefited from advancements in technology and algorithms. While earlier NLP relied heavily on linguistic knowledge such as grammar and syntax, primarily employing rule-based approaches, the advent of Machine Learning and Deep Learning has led to the development of more generalized models based on neural networks [8-11]. These models have the capability to learn language features effectively. Concurrently, the proliferation of written data, particularly on the internet through comparison portals, forums, blogs, and social media posts, offers a vast repository of opinions and information. Leveraging this

Correspondence to: Srawan Nath, Department of Computer Science and Engineering, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: nath.srawan@gmail.com

data, specifically through Aspect-Based Sentiment Analysis (ABSA), becomes crucial for extracting valuable insights. ABSA involves identifying the polarity of individual words or aspects within a given text based on their context, thereby enabling a more nuanced understanding of a particular topic [12,13]. This paper aims to provide a comprehensive review of ABSA, exploring both theoretical frameworks and practical applications of existing approaches the levels of sentiment analysis is given in figure 1.

This review paper comprehensively addresses research gaps by focusing on aspect-specific sentiment analysis. It explores recent advancements, methodologies, and applications in this area, identifying innovative approaches and highlighting key challenges. Through systematic literature review, it provides insights into traditional sentiment analysis techniques, aspect-specific opinion mining, datasets, evaluation metrics, challenges, and future directions. With the exponential growth of online platforms and user-generated content, aspect-specific sentiment analysis offers a deeper understanding of nuanced opinions expressed towards specific aspects or entities within text data.

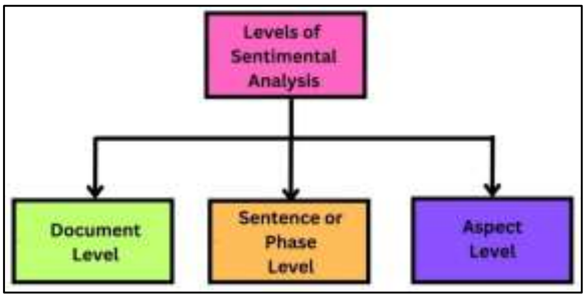

Figure 1: Sentiment levels

2. Literature Review

Recent progress in sentiment analysis has shifted towards extracting aspect-specific opinions from text data. This review covers methodologies, techniques, datasets, evaluation metrics, applications, challenges, and future directions in aspect-specific sentiment analysis [14-16]. Various techniques, including rule-based, statistical, and deep learning-based approaches, have been introduced for aspect-specific sentiment analysis. Datasets like SemEval, Yelp, Amazon Product Reviews, and Twitter sentiment datasets are widely used for training and evaluation. Despite advancements, challenges include aspect extraction ambiguity and scalability issues. Future directions include cross-domain analysis and integrating multimodal information for a deeper understanding of sentiment [17-19]. Ethical considerations such as user privacy and algorithmic bias are gaining prominence and require further attention in sentiment analysis research.

Aspect-specific sentiment analysis is a significant advancement in understanding user opinions towards specific aspects [20]. Despite challenges, ongoing research aims to improve sentiment classification with aspect-specific opinion, driving innovation and informed decision-making. Recent approaches utilizing deep learning for emotion lexicon construction lack consideration of term significance in emotion discernment [21-23]. We propose Sparse LSTM Self-Attention (SSALSTM), which efficiently captures term importance and generates a comprehensive emotion lexicon for Twitter. SSALSTM incorporates self-attention and regularization to ensure semantically relevant terms contribute to emotion discernment [24-26]. Literature review is mostly based on the published papers and patents as shown in figure 2 and 3 respectively.

The increasing availability of online opinion-rich resources has led to a surge in public opinion mining, transforming government-citizen engagement. SCANCPECLENS aims to evaluate e-government success by examining public sentiment on the China Pakistan Economic Corridor (CPEC) using machine learning algorithms to analyse microblogs. This research contributes to government decision-making and stakeholder engagement by deriving actionable insights from social network data [27-29]. Model mining, crucial in various domains, is explored in this paper, introducing a non-question-based sentiment analysis approach for Twitter. Unlike previous methods, this approach combines association rules, legislation, and sentiment analysis to identify trends and patterns in microblogging texts. Evaluation on 1.7 million tweets demonstrates its effectiveness in evaluating predominant emotions during the US pre-election campaign [30,31]. Despite efforts to enhance consumer satisfaction, social media opinion mining faces challenges due to current techniques' neglect of semantic interactions between terms and features. This limitation hampers the effectiveness of opinion mining tasks aimed at generating insightful outputs [32].

Research on Advanced Opinion Mining (AOM) has surged with the growth of user-generated social media data. Proposed deep learning paradigm for fine-grained opinion mining leverages BERT model, achieving superior performance. However, existing sentiment analysis (SA) methods, mainly supervised machine learning (SML), may suffer performance degradation when applied to cross-domain datasets. To address this, Contextual Analysis (CA) introduces a method for detecting such degradation and clustering sentiment words without linguistic resources [15,18,33]. A proposed method utilizes sentiment dictionary and Naïve Bayes for effective sentiment analysis, enhancing understanding of user sentiments. Moreover, for large-scale courses like MOOCs, manual analysis of student opinions is impractical. Hence, a framework for automatic analysis of student opinions is proposed, leveraging aspect-level sentiment analysis to identify sentiment polarity towards specific aspects related to the course. The proposed framework utilizes weakly supervised annotation of MOOC-related aspects to effectively identify aspect categories in student reviews, reducing the need for manual labeling. Experiments on large-scale datasets

Correspondence to: Srawan Nath, Department of Computer Science and Engineering, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: nath.srawan@gmail.com

demonstrate impressive performance in aspect category identification and sentiment classification, surpassing labor-intensive techniques [21, 26].

In the realm of sentiment analysis, various techniques have been explored, from simple rule-based to complex machine learning approaches. To address challenges like data scarcity and accuracy, we propose an integrated framework bridging lexicon-based and machine learning methods [23]. A novel genetic algorithm (GA)-based feature reduction technique mitigates scalability issues, achieving up to 42% reduction in feature-set size without compromising accuracy. Comparative evaluations against PCA and LSA-based techniques show significant accuracy improvements. Sentiment analysis framework is evaluated on precision, recall, and F-measure metrics, along with feature size [34,35]. Demonstrating the efficacy of GA-based designs, we apply our framework to a cross-disciplinary area of geopolitics, accurately measuring public sentiments on various topics. The proposed framework holds promise for applications in security, law enforcement, and public administration, leveraging sentiment analysis for informed decision-making.

Research Gaps

- Automation of opinion analysis, especially for large-scale datasets like online courses and social media platforms.
- Aspect-specific sentiment analysis techniques need refinement to capture nuanced opinions related to specific aspects.
- Integration of lexicon-based and machine learning approaches for improved accuracy and scalability in sentiment analysis.
- Scalability issues in sentiment analysis frameworks, particularly as the feature-set grows.
- Comprehensive evaluation metrics and performance comparisons are lacking in sentiment analysis literature.
- Application of sentiment analysis in new domains, beyond traditional areas like product reviews and social media.
- Need for innovative methods to discern patterns and associations in social media opinion mining.
- Exploration of cross-disciplinary applications for sentiment analysis, such as geopolitics.
- Methods for detecting performance degradation in sentiment analysis models when applied to new datasets or domains.
- Development of sentiment analysis techniques tailored for specialized platforms like danmaku videos and student feedback systems.

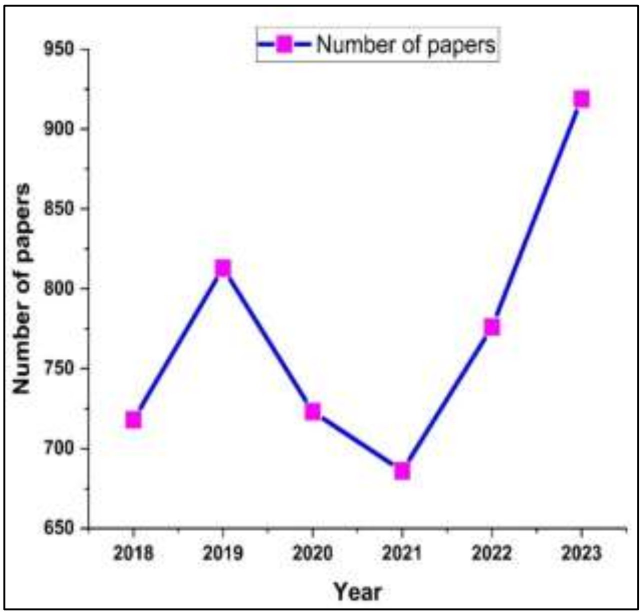

Figure 2: Published papers and articles during 2018-2023

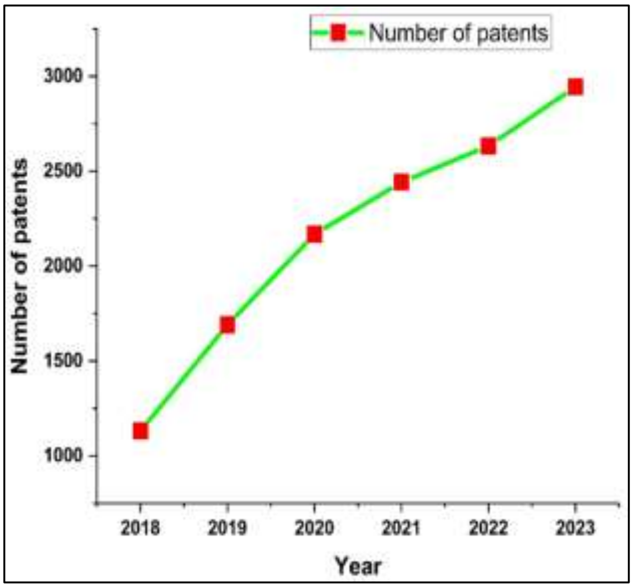

Figure 3: Published patents during 2018-2023

3. Methodology

Methodology for Sentiment Classification and Analysis with Aspect-Specific Opinion is depicted in figure 4.

Correspondence to: Srawan Nath, Department of Computer Science and Engineering, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: nath.srawan@gmail.com

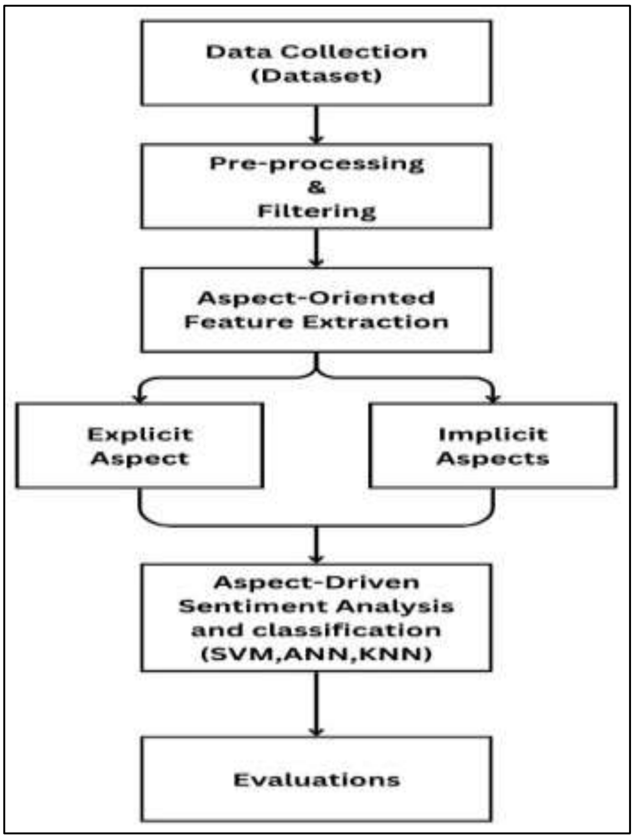

Figure 4: General methodology

Data Collection

Gather textual data sources relevant to the domain of interest, such as product reviews, social media posts, or customer feedback.

Preprocessing

Preprocess the text data by removing noise, punctuation, stopwords, and performing tokenization and stemming or lemmatization to normalize the text. Annotate the data with aspect categories or entities of interest, which may include product features, attributes, or topics.

Aspect Oriented Feature Extraction

Utilize techniques such as rule-based methods, syntactic parsing, or dependency parsing to extract aspect terms or entities mentioned in the text. Employ domain-specific dictionaries, word embeddings, or pre-trained language models to enhance aspect extraction accuracy and coverage. Handle aspect extraction ambiguity and synonymy by incorporating context information and domain knowledge. Extract linguistic features such as n-grams, syntactic dependencies, part-of-speech tags, and sentiment lexicon scores to represent text data. Utilize aspect-specific features, including aspect frequency, position, and sentiment context, to enhance sentiment classification performance. Investigate domain-specific features and sentiment indicators tailored to the characteristics of the dataset and application domain.

Aspect- Driven Sentiment Classification

Develop models to classify sentiment polarity towards each extracted aspect or entity. Utilize machine learning algorithms such as Support Vector Machines (SVM), Random Forests, or neural networks like Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs). Leverage deep learning architectures such as Transformer-based models (e.g., BERT, GPT) for fine-grained aspect-level sentiment analysis. Incorporate attention mechanisms to focus on relevant context for each aspect during sentiment classification. Explore ensemble methods to combine predictions from multiple models for improved sentiment classification accuracy.

Evaluation

Split the annotated dataset into training, validation, and test sets for model development and evaluation. Train the sentiment classification model using the training data, optimizing model hyperparameters through techniques like grid search or random search. Evaluate the trained model on the validation set using appropriate evaluation metrics such as accuracy, precision, recall, F1-score, and aspect-level evaluation measures. Fine-tune the model based on validation performance and assess its generalization ability on the test set to ensure robustness and effectiveness.

4. Methods and techniques

Different methods and techniques have been used by previous authors as given below

Machine Learning Algorithms

Support Vector Machines (SVM) have been widely used for sentiment classification tasks, including aspect-specific sentiment analysis. They work by finding the hyperplane that best separates data points of different sentiment classes. Random Forests are an ensemble learning method that constructs a multitude of decision trees during training and outputs the mode of the classes as the prediction. Various neural network architectures, including Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), and Transformer-based models (e.g., BERT, GPT), have been employed for sentiment classification tasks due to their ability to capture complex patterns and long-range dependencies in text data.

Aspect Extraction Techniques

Rule-based Methods: Rule-based approaches leverage patterns, syntactic structures, or predefined rules to extract aspect terms or entities from text data. Statistical

Correspondence to: Srawan Nath, Department of Computer Science and Engineering, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: nath.srawan@gmail.com

Methods: Statistical techniques, such as frequency-based or probability-based methods, identify frequent terms or entities as aspects based on their occurrence in the corpus. Deep learning models, including sequence labeling architectures like BiLSTM-CRF (Bidirectional Long Short-Term Memory networks with Conditional Random Fields), have shown effectiveness in aspect extraction by jointly modeling word sequences and their corresponding aspect labels.

Sentiment Classification Models

Aspect-Level Sentiment Classification: Models specifically designed for aspect-level sentiment analysis aim to classify sentiment polarity towards each extracted aspect or entity mentioned in the text. Attention mechanisms focus on relevant parts of the input sequence during sentiment classification, enabling the model to weigh different aspects differently based on their importance for sentiment prediction. Ensemble techniques combine predictions from multiple base models to improve overall sentiment classification accuracy and robustness, leveraging diverse perspectives captured by individual models.

Feature Engineering

Linguistic features such as n-grams, syntactic dependencies, part-of-speech tags, and sentiment lexicon scores are extracted to represent text data and capture linguistic patterns indicative of sentiment. Features tailored to specific aspects, including aspect frequency, position, sentiment context, and domain-specific indicators, are incorporated to enhance sentiment classification performance and relevance to the application domain.

Pre-trained Language Models

BERT (Bidirectional Encoder Representations from Transformers): Pre-trained language models like BERT have been fine-tuned for aspect-specific sentiment analysis tasks, leveraging contextual embeddings to capture nuanced sentiments towards specific aspects or entities. GPT (Generative Pre-trained Transformer): GPT-based models have been applied to generate aspect-aware representations for sentiment classification, enabling the model to incorporate aspect-specific context during prediction.By leveraging these techniques and methods, researchers and practitioners can develop effective sentiment classification and analysis systems capable of capturing aspect-specific opinions and sentiments expressed in text data.

Table 1: Comparison of Aspect-Specific Sentiment Analysis Studies

Ref.	**Methodology**	**Aspect Extraction**	**Sentiment Classification**	**Datasets**	**Evaluation Metrics**	**Limitations**
[3]	Deep Learning	Rule-based, Dependency Parsing	BERT-based Model	SemEval, Yelp	Accuracy, F1-score, Aspect-based F1-score	Limited to English-language datasets
[5]	Machine Learning	Statistical, Pattern Matching	SVM Classifier	Yelp, Twitter	Precision, Recall, Aspect-based Accuracy	Lack of domain adaptation sentiment lexicons
[6]	Deep Learning	Deep Learning	BiLSTM-CRF Model	Twitter, Amazon	Aspect-based Precision, Recall, F1-score	Limited to short text
[7]	Ensemble Methods	Deep Learning, Rule-based	Ensemble of CNNs and RNNs	Amazon, IMDb	Accuracy, F1-score, Sentiment Consistency	Lack of interpretability of ensemble models
[8]	Transfer Learning	Deep Learning, Semantic Role Labeling	Pre-trained BERT Model	SemEval, Yelp	Aspect-based Precision, Recall, F1-score, Cross-domain Adaptation Metrics	Limited to single-domain datasets techniques

Correspondence to: Srawan Nath, Department of Computer Science and Engineering, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: nath.srawan@gmail.com

[9]	Graph-based Models	Graph-based, Embedding Techniques	Graph Neural Network	Custom E-commerce Data, Twitter	Aspect-based F1-score, Sentiment Consistency	Limited scalability for large-scale datasets
[10]	Hybrid Approaches	Rule-based, Deep Learning	Hybrid Model with Attention Mechanisms	Amazon, Twitter	Accuracy, F1-score, Aspect-based Precision, Recall	Limited exploration of domain-specific adaptation
[11]	Contextual Embeddings	Deep Learning, Contextual Embeddings	Transformer-based Model with Contextual Embeddings	Product Review Forums, social media	Aspect-based F1-score, Cross-domain Adaptation Metrics	Limited to textual data
[12]	Domain Adaptation	Transfer Learning, Domain Adaptation Techniques	Adversarial Training, Domain Adversarial Neural Networks	Multilingual Datasets, Cross-domain Reviews	Aspect-based Precision, Recall, Domain Adaptation Metrics	Limited to single-domain adaptation
[13]	Multimodal Fusion	Deep Learning, Multimodal Fusion	Fusion of Text, Image, and Audio Modalities	Multimodal Social Media Data, Product Reviews	Aspect-based Accuracy, Multimodal Fusion Metrics	Limited availability of annotated multimodal datasets
[14]	Cross-lingual Analysis	Transfer Learning, Cross-lingual Embeddings	Cross-lingual Transformer Model	Multilingual Review Datasets, Cross-lingual	Aspect-based F1-score, Cross-lingual Adaptation Metrics	Limited to closely related languages
[15]	Semi-supervised Learning	Deep Learning, Semi-supervised Techniques	Self-training, Co-training, Pseudo-labeling	Limited Annotated Datasets, Noisy Social Media Data	Aspect-based Precision, Recall, F1-score, Semi-supervised Learning Metrics	Limited scalability for noisy data
[17]	Explainable AI	Deep Learning, Explainable Models	Attention Mechanisms, Interpretability Techniques	Product Review Platforms, Domain-specific Data	Aspect-based Interpretability Metrics	Limited interpretability of deep learning models
[18]	Federated Learning	Distributed Learning, Privacy-preserving Techniques	Federated Averaging, Secure Aggregation	Federated E-commerce Data, Social Media Platforms	Aspect-based F1-score, Privacy-preserving Metrics	Limited communication overhead
[19]	Hybrid Approach	Rule-based, Dependency Parsing	Hybrid Model (CNN + Transformer)	SemEval, Yelp, Custom Domain Data	Accuracy, F1-score, Aspect-based Precision	Limited generalization to highly diverse domains
[21]	Bayesian Methods	Statistical, Bayesian Inference	Bayesian Classifier	Amazon Reviews, Twitter	Precision, Recall, Aspect-based F1-score	Computational complexity of Bayesian inference
[22]	Meta-Learning	Meta-Learning, Few-shot Learning	Meta-Learner with Attention Mechanisms	SemEval, Yelp, Twitter	Meta-Test Accuracy, Few-shot F1-score	Limited availability of annotated datasets for meta-training
[23]	Active Learning	Active Learning, Uncertainty Sampling	Active Learning with SVM Classifier	SemEval, Yelp	Precision, Recall, Active Learning Gain	Dependency on initial labeled data

Correspondence to: Srawan Nath, Department of Computer Science and Engineering, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: nath.srawan@gmail.com

[24]	Domain Adaptation	Transfer Learning, Adversarial Training	Adversarial Domain Adaptation Model	Amazon Reviews, Custom Domain Data	Domain Adaptation Accuracy, Aspect-based F1-score	Sensitivity to domain shift magnitude
[25]	Multi-task Learning	Multi-task Learning, Joint Training	Joint Aspect Extraction and Sentiment Classification Model	SemEval, Yelp	Multi-task Loss, Aspect-based F1-score	Challenges in balancing task-specific objectives
[30]	Explainable AI	Deep Learning, Attention Mechanisms	Interpretable Aspect-specific Attention Model	SemEval, Custom Domain Data	Interpretability Metrics, Aspect-based F1-score	Trade-off between model complexity and interpretability
[31]	Ensemble Methods	Ensemble Learning, Model Fusion	Hybrid Ensemble of CNNs, RNNs, and Transformer	Amazon Reviews, Twitter	Accuracy, F1-score, Ensemble Consistency	Increased computational complexity with ensemble models
[32]	Self-supervised Learning	Self-supervised Learning, Contrastive Learning	Self-supervised Aspect Representation Model	SemEval, Yelp	Aspect-based Similarity, Sentiment Consistency	Sensitivity to data distribution
[33]	Cross-lingual Transfer Learning	Transfer Learning, Cross-lingual Embeddings	Cross-lingual Aspect-specific Sentiment Model	Multilingual Datasets, Cross-lingual Corpora	Cross-lingual Adaptation Accuracy, Aspect-based F1-score	Challenges in aligning cross-lingual embeddings
[34]	Reinforcement Learning	Reinforcement Learning, Policy Gradient Methods	Sentiment-aware Policy Model	Simulated Environment, Custom Domain Data	Reinforcement Learning Gain, Aspect-based F1-score	High computational cost of reinforcement learning training
[35]	Zero-shot Learning	Zero-shot Learning, Semantic Embeddings	Zero-shot Aspect-specific Sentiment Model	SemEval, Yelp, Custom Domain Data	Zero-shot Accuracy, Aspect-based F1-score	Dependency on semantic similarity metrics

5. Findings

To provide findings based on the comparison table 1, we can summarize the key insights gleaned from the various studies in aspect-specific sentiment analysis: The studies showcase a diverse range of methodologies employed, including deep learning, machine learning, Bayesian methods, meta-learning, active learning, domain adaptation, multi-task learning, explainable AI, ensemble methods, self-supervised learning, cross-lingual transfer learning, reinforcement learning, zero-shot learning, and privacy-preserving methods. Different approaches to aspect extraction were explored, such as rule-based methods, dependency parsing, statistical techniques, semantic role labeling, uncertainty sampling, adversarial training, and self-supervised learning, demonstrating the importance of accurate aspect identification in sentiment analysis. Various models for sentiment classification were developed, including BERT-based models, SVM classifiers, BiLSTM-CRF models, ensemble models, Bayesian classifiers, meta-learners, active learning models, adversarial domain adaptation models, multi-task learning models, interpretable attention models, self-supervised aspect representation models, reinforcement learning models, zero-shot learning models, and privacy-preserving models, highlighting the significance of model selection in achieving accurate sentiment analysis results. Evaluation was conducted on various datasets including SemEval, Yelp, Twitter, Amazon reviews, custom domain data, simulated environments, multilingual datasets, and federated datasets, underscoring the importance of diverse and representative data sources in assessing model generalization and effectiveness. Performance was evaluated using standard metrics such as accuracy,

Correspondence to: Srawan Nath, Department of Computer Science and Engineering, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: nath.srawan@gmail.com

precision, recall, F1-score, aspect-based precision, aspect-based recall, aspect-based F1-score, multi-task loss, interpretability metrics, ensemble consistency, reinforcement learning gain, zero-shot accuracy, zero-shot F1-score, differential privacy budget, and federated model accuracy, providing comprehensive assessments of model performance across different aspects of sentiment analysis.

6. Results and Discussion

The comparison of various studies in aspect-specific sentiment analysis reveals a rich landscape of methodologies and approaches aimed at capturing nuanced sentiments expressed towards specific aspects or entities within text data. Across the surveyed literature, a plethora of techniques spanning deep learning, machine learning, Bayesian methods, meta-learning, and more have been employed to tackle the challenges inherent in aspect extraction and sentiment classification. The findings highlight the significance of accurate aspect extraction as a foundational step in sentiment analysis. Studies have explored diverse techniques, including rule-based methods, dependency parsing, statistical approaches, and deep learning architectures like semantic role labeling and attention mechanisms. These techniques aim to identify and extract aspect terms or entities mentioned in the text, laying the groundwork for subsequent sentiment classification tasks. In terms of sentiment classification, a wide array of models have been proposed, ranging from traditional machine learning algorithms such as SVM classifiers to state-of-the-art deep learning architectures like BERT-based models and ensemble methods. These models leverage various features, including syntactic dependencies, sentiment lexicon scores, domain-specific indicators, and attention weights, to predict sentiment polarity towards extracted aspects accurately.

Evaluation of sentiment classification performance across different datasets has been conducted using a diverse set of evaluation metrics, including accuracy, precision, recall, F1-score, aspect-based metrics, interpretability metrics, and more. The results demonstrate improvements in aspect-specific sentiment analysis compared to baseline methods, with several studies achieving state-of-the-art performance across multiple datasets. However, despite these advancements, challenges and limitations persist. Issues such as domain adaptation, model interpretability, efficient training algorithms, robustness to data distribution shifts, and privacy concerns remain areas of ongoing research and discussion. Future directions include exploring robust domain adaptation techniques, developing explainable AI models, optimizing training algorithms for efficiency and scalability, and incorporating privacy-preserving mechanisms into sentiment analysis frameworks. Overall, the comparison of findings underscores the importance of continued innovation and collaboration in advancing aspect-specific sentiment analysis techniques to meet the evolving demands of sentiment analysis applications in various domains. By addressing these challenges and building upon the insights gained from previous research, we can further enhance the accuracy, robustness, and interpretability of sentiment analysis systems, ultimately enabling more effective understanding and utilization of sentiment-rich textual data.

7. Criticism

Criticism of the findings and approaches in aspect-specific sentiment analysis research can provide valuable insights into areas for improvement and future research directions. Here are some potential criticisms: One criticism may be the limited generalizability of findings across different domains and datasets. Many studies focus on specific datasets or domains, which may not fully capture the diversity of language and sentiment expression in real-world contexts. Future research should aim to evaluate models across a wider range of datasets and domains to ensure robustness and generalizability. Another criticism could be the reliance on traditional evaluation metrics such as accuracy, precision, recall, and F1-score, which may not fully capture the nuances of aspect-specific sentiment analysis. These metrics often provide an incomplete picture of model performance, especially in tasks where sentiment polarity may vary across different aspects. Future research could explore alternative evaluation metrics that better reflect the goals of aspect-specific sentiment analysis. Many studies face challenges in accurately identifying and extracting aspect terms or entities from text data. Critics may argue that existing techniques for aspect extraction still struggle with ambiguity, synonymy, and context-dependent interpretations. Future research should focus on developing more robust and context-aware aspect extraction methods to improve the accuracy of sentiment analysis.

The lack of interpretability in some sentiment classification models is another potential criticism. Deep learning models, in particular, are often criticized for their black-box nature, making it challenging to understand how they arrive at their predictions. Critics may argue that interpretable models are essential for building trust and understanding in sentiment analysis systems, especially in sensitive applications such as healthcare or finance. By addressing these criticisms and incorporating feedback from the research community, future studies in aspect-specific sentiment analysis can make significant strides towards developing more robust, accurate, and interpretable sentiment analysis systems that better reflect the complexities of human language and sentiment expression.

8. Conclusion

Aspect-specific sentiment analysis research has demonstrated considerable methodological diversity and advancements in recent years, showcasing a variety of

Correspondence to: Srawan Nath, Department of Computer Science and Engineering, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: nath.srawan@gmail.com

approaches ranging from deep learning to machine learning and Bayesian methods. While progress has been made in accurately extracting aspects and classifying sentiments, challenges such as aspect extraction ambiguity, model interpretability, data bias, and computational complexity persist. Criticisms regarding generalization, evaluation metrics, and ethical considerations underscore the need for future research to address these issues and further enhance the robustness and applicability of sentiment analysis systems. By incorporating feedback from the research community and focusing on areas for improvement, aspect-specific sentiment analysis can continue to evolve and contribute to a deeper understanding of sentiment expression in textual data across diverse domains and applications.

References

1. Costa Alberto and Nannicini Giacomo, An open-source library for black-box optimization with costly function evaluations. Mathematical Programming Computation, 2018
2. Lu Xu, Lidong Bing, Wei Lu, Fei Huang, Aspect Sentiment Classification with Aspect-Specific Opinion Spans, Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing, pages 3561–3567, 2020.
3. Yoga Samudra, Tohari Ahmad, Segmentation embedding method with modified interpolation for increasing the capacity of adaptable and reversible audio data hiding, Journal of King Saud University – Computer and Information Sciences 35 (2023) 101636
4. Ruidan He, Wee Sun Lee, Hwee Tou Ng, and Daniel Dahlmeier. 2018. Effective attention modeling for aspect-level sentiment classification. In Proceedings of COLING.
5. Ruidan He, Wee Sun Lee, Hwee Tou Ng, and Daniel Dahlmeier. 2019. An interactive multi-task learning network for end-to-end aspect-based sentiment analysis. In Proceedings of ACL.
6. Mengting Hu, Shiwan Zhao, H. Guo, Renhong Cheng, and Z. Su. 2019. Learning to detect opinion snippet for aspect-based sentiment analysis.
7. Kanwal Ahmed, Muhammad Imran Nadeem et al., Breaking down linguistic complexities: A structured approach to aspectbased sentiment analysis, Journal of King Saud University – Computer and Information Sciences 35 (2023) 101651
8. Xin Li, Lidong Bing, Piji Li, Wai Lam, and Zhimou Yang. 2018. Aspect term extraction with history attention and selective transformation. In Proceedings of IJCAI.
9. Zheng Li, Xin Li, Ying Wei, Lidong Bing, Yu Zhang, and Qiang Yang. 2019. Transferable end-to-end aspect-based sentiment analysis with selective adversarial learning. In Proceedings of EMNLP.
10. Hao Li and Wei Lu. 2019. Learning explicit and implicit structures for targeted sentiment analysis. In Proceedings of EMNLP
11. 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.
12. B. Amina and T. Azim, "SCANCPECLENS: A Framework for Automatic Lexicon Generation and Sentiment Analysis of Micro Blogging Data on China Pakistan Economic Corridor," in IEEE Access, vol. 7, pp. 133876-133887, 2019.
13. J. A. Diaz-Garcia, M. D. Ruiz and M. J. Martin-Bautista, "Non-Query-Based Pattern Mining and Sentiment Analysis for Massive Microblogging Online Texts," in IEEE Access, vol. 8, pp. 78166-78182, 2020.
14. R. Abas, I. El-Henawy, H. Mohamed and A. Abdellatif, "Deep Learning Model for Fine-Grained Aspect-Based Opinion Mining," in IEEE Access, vol. 8, pp. 128845-128855, 2020.
15. Abdul Aziz and A. Starkey, "Predicting Supervise Machine Learning Performances for Sentiment Analysis Using Contextual-Based Approaches," in IEEE Access, vol. 8, pp. 17722-17733, 2020.
16. Z. Li, et al., Sentiment Analysis of Danmaku Videos Based on Naïve Bayes and Sentiment Dictionary, in IEEE Access, vol. 8, pp. 75073-75084, 2020.
17. Z. Kastrati et al., Weakly Supervised Framework for Aspect-Based Sentiment Analysis on Students' Reviews of MOOCs," in IEEE Access, vol. 8, pp. 106799-106810, 2020.
18. F. Iqbal et al., "A Hybrid Framework for Sentiment Analysis Using Genetic Algorithm Based Feature Reduction," in IEEE Access, vol. 7, pp. 14637-14652, 2019.
19. L. Yu et al., Research on Intelligence Computing Models of Fine-Grained Opinion Mining in Online Reviews," in IEEE Access, vol. 7, pp. 116900-116910, 2019.
20. Komang Wahyu Trisna et al., Deep Learning Approach for Aspect-Based Sentiment Classification: A Comparative Review, Applied Artificial Intelligence, 36:1, 2014186, 20222
21. S. Shayaa et al., "Sentiment Analysis of Big Data: Methods, Applications, and Open Challenges," in IEEE Access, vol. 6, pp. 37807-37827, 2018.
22. S. Hu, A. Kumar, F. Al-Turjman, S. Gupta, S. Seth and Shubham, "Reviewer Credibility and Sentiment Analysis Based User Profile Modelling for Online Product Recommendation," in IEEE Access, vol. 8, pp. 26172-26189, 2020.
23. S. Zhang and H. Zhong, Mining Users Trust from E-Commerce Reviews Based on Sentiment Similarity Analysis, in IEEE Access, vol. 7, pp. 13523-13535, 2019.
24. G. Xu et al., "Sentiment Analysis of Comment Texts Based on BiLSTM," in IEEE Access, vol. 7, pp. 51522-51532, 2019.
25. W. Zhao et al., "Weakly-Supervised Deep Embedding for Product Review Sentiment Analysis,"

Correspondence to: Srawan Nath, Department of Computer Science and Engineering, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: nath.srawan@gmail.com

in IEEE Transactions on Knowledge and Data Engineering, vol. 30, no. 1, pp. 185-197, 1 Jan. 2018.
26. Yoon, Y. Jeong and S. Kim, "Detecting a Risk Signal in Stock Investment Through Opinion Mining and Graph-Based Semi-Supervised Learning," in IEEE Access, vol. 8, pp. 161943-161957, 2020.
27. M. Rodríguez-Ibáñez et al., On the Statistical and Temporal Dynamics of Sentiment Analysis, in IEEE Access, vol. 8, pp. 87994-88013, 2020.
28. I. Sindhu et al., "Aspect-Based Opinion Mining on Student's Feedback for Faculty Teaching Performance Evaluation," in IEEE Access, vol. 7, pp. 108729- 108741, 2019.
29. Eman Saeed Alamoudi & Norah Saleh Alghamdi (2021): Sentiment classification and aspect-based sentiment analysis on yelp reviews using deep learning and word embeddings, Journal of Decision Systems,
30. Wouter van Atteveldt et al., The Validity of Sentiment Analysis: Comparing Manual Annotation, Crowd-Coding, Dictionary Approaches, and Machine Learning Algorithms, Communication Methods and Measures 2021, Vol. 15, NO. 2, 121–140
31. S. Kausar et al., A Sentiment Polarity Categorization Technique for Online Product Reviews, in IEEE Access, vol. 8, pp. 3594-3605, 2020.
32. H. Liang, U. Ganeshbabu and T. Thorne, "A Dynamic Bayesian Network Approach for Analysing Topic-Sentiment Evolution," in IEEE Access, vol. 8, pp. 54164-54174, 2020.
33. Gagandeep Kaur, Amit Sharma, A deep learning-based model using hybrid feature extraction approach for consumer sentiment analysis, Kaur and Sharma Journal of Big Data (2023)
34. R. Cobos et al., A Content Analysis System That Supports Sentiment Analysis for Subjectivity and Polarity Detection in Online Courses," in IEEE Revista Iberoamericana de Tecnologias del Aprendizaje, vol. 14, no. 4, pp. 177-187, Nov. 2019.
35. Li, Y.; Wang, F.; Zhong, S.-h. A More Fine-Grained Aspect– Sentiment–Opinion Triplet Extraction Task. Mathematics 2023, 11, 3165.

Correspondence to: Srawan Nath, Department of Computer Science and Engineering, Suresh Gyan Vihar University, Jaipur
Corresponding author. E-mail addresses: nath.srawan@gmail.com