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Research Trends on Sentiment Analysis and Imbalanced Data Handling in Fake Review Detection: A Systematic Literature Review

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Abstract Fake reviews are deceptive evaluations that mislead customers rather than reflect genuine customer experiences. These reviews can damage the business's reputation by deceiving the customers, which then causes them to make poor decisions about what to buy and diminishes the trust that e-commerce platforms can have. Detecting fake reviews is crucial for e-commerce platforms to maintain their integrity, protect consumers, and uphold business reputations. Despite its importance, there is a paucity of comprehensive research addressing fake review detection through the lenses of Sentiment Analysis (SA) and imbalanced data handling. To bridge this gap, a systematic literature review uses Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. This review analyzed 43 studies from the Scopus and Web of Science databases, covering the period from 2019 to 2024. Three primary themes emerged: SA levels, detection methods, and techniques for handling imbalanced data, which further branched into 28 sub-themes. The analysis revealed key trends such as a predominant focus on document-level SA, the application of machine learning approaches, and data resampling techniques to address imbalanced datasets. The review underscored the necessity for more research on aspect-level analysis and the development of combinational approaches, such as hybrid models, to enhance the accuracy and reliability of fake review detection. These insights provide valuable guidance for researchers, data scientists, and developers seeking to advance the field.

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1 Introduction

E-commerce platforms have become necessary in the digital era so that businesses can reach the consumers. They have revolutionized the way the consumers make their buying choices, in large part, because of the presence of peer reviews [1]. Nevertheless, with the rising popularity of e-commerce, there have been some questions of fraud and fraudulent activities, such as counterfeit reviews, which have eroded confidence and forced the adoption of stringent cybersecurity protocols to guard consumers and businesses against such activities [2] and similar. In this way, this brought to the fore the problem of bogus reviews which can misinform consumers, hurt the reputation of businesses and the credibility of online platforms themselves [3].

The fake reviews are emotional and do not specify the product, which is why they are difficult to identify correctly [4]. Their sophisticated writing styles and use of subtle indicators also make it even more difficult to detect them and it takes more sophisticated methods than conventional methods. Such reviews have complexities, so traditional SA methods are not very effective in detection accuracy and efficiency.

Machine learning (ML) has been extensively used by researchers to identify fake reviews, based on textual characteristics including language style, punctuations, and phrasing, and behavioral patterns including frequency and length of reviews among others [5]. Its ability to process large datasets and uncover patterns makes it a crucial tool for advanced techniques such as Sentiment Analysis (SA). SA is a process that uses Natural Language Processing (NLP), text analysis, and computational linguistics to identify, extract, and analyze subjective information in text-based data [6]. SA is known to have three different levels, including document level, sentence level, and an aspect or feature level [7]. SA can determine the general sentiment of a text at the document and sentence level. However, it does not consider specific entities such as products, services, or people and their attributes that may be mentioned in the text [8]. This implies that while SA can identify if the review is positive or negative, it does not automatically parse which aspects of a product or service are good or bad or even which specific product or service is being discussed, without additional contextual or entity-specific analysis. Therefore, it is important to identify the most suitable implementation of SA to detect the sentiment of each product mentioned in reviews and the techniques used to distinguish between fake and genuine reviews.

Another major issue in this research is the challenge of fake reviews being less common than real reviews, where the number of fake reviews is significantly lower than the number of genuine reviews [9]. This leads to the imbalanced dataset problem. Authors in [10] reveal that learning techniques that do not prioritize minority or fake samples may perform poorly in identifying fake reviews, even though the algorithm's overall accuracy is quite high. In text classification, imbalanced data can cause algorithms to achieve high accuracy by focusing on the majority class while failing to accurately detect fake reviews. This highlights the need for specialized techniques to address this challenge.

Nevertheless, it is necessary to conduct a thorough analysis of these works and determine the trends and future topics associated with the issue. The processes of review were not effectively coordinated which comprised of identification, screening and eligibility. The common literature reviews commonly used have been criticized as being subjective, potentially biased and lacking transparency as opposed to systematic literature reviews [11, 15–17]. Therefore, it is vital that a more systematic literature review (SLR) analysis is necessary.

In recent years, a number of review studies on fake review detection have been carried out, with most of them being based on general machine learning and deep learning methods to perform classification tasks. The studies do not focus on the levels of sentiment analysis performance and the effects of unbalanced datasets on the performance of the detector, but rather they usually focus on model performance, feature engineering, and detection accuracy. Conversely, the currently undertaken paper offers a more narrow and integrative viewpoint, by collectively examining the sentiment analysis (SA) levels and unbalanced data processing methods in fake review detection. This two-fold approach allows one to understand more about the effect of sentiment representation and data distribution issues on the detection findings, which has not been thoroughly studied in the previous review studies.

The paper will discuss several research studies done in the area of fake review detection and their research methods, limitations, and contributions. The analysis will consider different methods to provide valuable insights into the strengths and weaknesses of these studies. The focus will be on a comprehensive approach to address the significant gap in comprehensive research on SA and imbalanced data handling in fake review detection.

The current study aims to fill a gap in the literature by conducting an SLR focused on SA and imbalanced data handling in fake review detection. The authors conducted this systematic review methodology following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines, which can ensure transparency and thoroughness, contrasting with traditional literature reviews. The findings obtained through this approach can be used to identify gaps and suggest the direction of future research in this field. We set the primary research question that directs the aim: "What are the research trends on SA and imbalanced data handling in fake review detection?". Furthermore, understanding the trend in fake review detection research is important for enhancing the detection of fake reviews. Based on this topic, this SLR attempts to address the following research question:

Question 1: What is SA's current and most suitable implementation for detecting fake reviews?

Question 2: What are the commonly used methods or approaches for detecting fake reviews?

Question 3: What techniques do researchers use to handle imbalanced data in fake review detection?

2 Methods

SLR is a process of discovering, evaluating, and interpreting all available research on a specific research question, topic area, or phenomenon of interest [18]. It aims to offer a fair assessment of a study topic using reliable, exacting, and auditable methods. The SLR was established in this study using the PRISMA. PRISMA emphasized a standardized process for improving the quality of systematic reviews and meta-analyses [19]. Besides that, it directs authors to detail their review procedures precisely, the work done, and the conclusions, guaranteeing that each aspect of the research is transparently discussed [20]. There are four main steps for PRISMA: identification, screening, eligibility, and data abstraction and analysis, shown in Figure 1.

2.1 Identification

The identification stage is the first step in the systematic literature review (SLR) procedure. Identification refers to the systematic process of finding, selecting, and determining studies that meet predefined inclusion and exclusion criteria, ensuring the comprehensiveness and relevance of the review. This stage was conducted in March 2024 [21] to capture a wide breadth of literature related to the research topic. By systematically identifying relevant studies, this step lays the foundation for subsequent stages of the SLR, providing an overview of existing research, highlighting knowledge gaps, and offering insights for refining the review's focus.

In this study, we carefully select the initial search keywords to align with the study's objectives. The process of selecting the keywords was done in order to make sure that the search was precise and recalled the relevant studies as it is described in Table 1. The search strategy included searching two large academic databases (AD) Scopus and Web of Science (WoS) using structured and systematic search strings. These databases guaranteed availability of high quality and peer reviewed literature on the topic.

Using Scopus and WoS together will guarantee a wide scope and a uniform indexing standard, organized metadata, and reproducibility of the search procedure, which are essential to PRISMA-based systematic reviews. Although other such domain-specific repositories as the IEEE Xplore or the ACM Digital Library might offer some other conference records, they were excluded due to the fact that a significant proportion of the high-impact and widely-used conference proceedings are already indexed in Scopus, and it would be redundant to index them again, not to mention that it would disrupt the methodological consistency and manageability of the review process.

The search resulted in an initial set of 723 Scopus and 78 WoS studies, which indicates the wide range of available studies on the topic. The high number of preliminary results highlights the performance of the selected search terms and coverage that can be achieved in these databases. Identification stage plays an important role in making sure that the SLR fully represents the state of research and this gives it a very good foundation to screen, analyze, and synthesize in the later stages.

Table 1. Description of Academic Databases

AD	Search String
Scopus	(TITLE-ABS-KEY ("Fake reviews" OR "Spam reviews") AND TITLE-ABS-KEY ("Detection" OR "Classification"))
WoS	TS = (("Fake reviews" OR "Spam reviews") AND ("Detection" OR "Classification"))

Some of the keywords were selected according to the purpose of the research. This step entailed searching the databases at Scopus and WoS, with search terms as indicated in the Table above, Table 1. Search queries

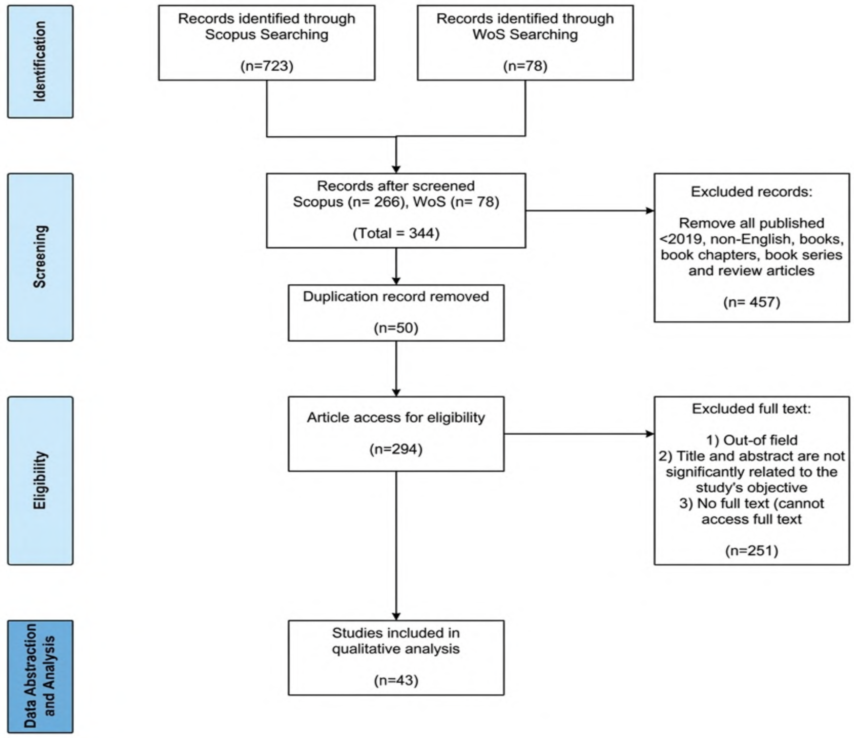

Figure 1. PRISMA Flow Diagram based on Online Database Identification

were formulated in such a way that they cover all the relevant studies and reduce irrelevant search results. Fake reviews and spam reviews were used interchangeably to encompass the differences in terms. Likewise, the terms of detection and classification were added to encompass various methods of fake review studies. It was an iterative search in which the preliminary search findings were examined and narrowed to enhance relevance and coverage.

2.2 Screening

After the identification process, a total of 801 articles were retrieved from Scopus and WoS databases based on the predefined search strings. These articles represent a wide range of literature relevant to the research topic, forming the initial dataset for the SLR. The PRISMA method was then employed to guide the screening process.

This method involves systematically applying inclusion and exclusion criteria to evaluate the relevance and quality of the retrieved articles, as shown in Table 2. The screening process aims to ensure that only the most suitable articles are included in the SLR, thereby enhancing the reliability and focus of the study.

First, the factor of inclusion is the publication timeline. The timelines that were chosen ranged from 2019 to 2024. Second, the excluded document types are systematic review journals, review papers, chapters in books, book series, and any books. The types that are included are only article journals and conference proceedings. The third criterion to be excluded is non-English. Non-English language was excluded to minimize misunderstandings and translation difficulties.

After applying these criteria, 457 articles were found to be irrelevant or unsuitable and were removed, leaving 344 articles for further analysis. Duplicate records were identified and eliminated to refine the dataset further. A total of 50 duplicate documents were detected and removed, resulting in a final pool of 294 unique articles that proceeded to the eligibility stage. This rigorous multi-step process ensured the final dataset's reliability, relevance, and focus, providing a solid foundation for the subsequent phases of the SLR.

2.3 Eligibility

The third step is the eligibility process, where the articles were included and excluded based on the author's specific criteria. The articles must be manually selected

Table 2. The Criteria for Inclusion and Exclusion

Criteria	Inclusion	Exclusion
Publication Timeline	2019–2024	2018 and before
Document Type	Journal (research articles), conference proceedings	Journals (systematic reviews), review papers, book chapters, book series, books
Language	English	Non-English

based on the most relevant research needed for this SLR. Articles not meeting the specific criteria will be eliminated from the retrieval process. Then, the authors will screen the potential studies based on the following criteria: 1) relevance to the field, 2) titles and abstracts, 3) availability of full text, and if they pass, the authors will then review the full-text articles to ensure that the criteria are met. Thus, the review obtained 43 articles related to fake review detection.

Other than that, to ensure the reliability and validity of the selected studies, a quality assessment process was conducted. A checklist adapted from established SLR guidelines [18] was used to evaluate each of the 43 selected articles.

2.4 Data Abstraction and Analysis

The fourth step is the data abstraction and analysis. To guarantee uniformity of all the selected studies, a systematic data extraction process was used. The important information in each of the 43 articles was systematically extracted, including year of publication, country, the extent of sentiment analysis (document, sentence, aspect), detection method (e.g., SVM, CNN, BERT), and imbalanced data processing method (e.g., resampling, SMOTE). The data were extracted and formatted as a matrix table to facilitate comparisons across the studies and facilitate further thematic analysis.

The single coding process based on a structured and predefined protocol was used to conduct the screening and thematic coding. The strategy provided uniformity in inclusion and exclusion criteria, data collection, and thematic coding of all the studies chosen. Even though formal inter-rater reliability estimates like Cohen Kappa were not used, the fact that a systematic and transparent procedure was used to minimize bias contributed to improving the reliability of the analysis.

The selected 43 articles were systematically reviewed and examined in detail to identify relevant patterns and insights. The analysis was based on studies that are directly relevant to the research objectives. This involved an initial screening of titles and abstracts, followed by a comprehensive review of the full-text articles.

The authors conducted a thematic analysis to uncover themes related to fake review detection. Thematic analysis is an approach often used in qualitative research to analyze data [22]. The 43 articles were categorized based on the main issues, similarities, and differences portrayed. Six steps were followed in the thematic analysis to construct themes in this SLR study, as proposed by [23]. The steps include:

1. **Familiarization with the data**: Understanding and analyzing the 43 selected articles.
2. **Generating initial codes**: Identifying similarities and differences among the issues discussed in the selected articles.
3. **Creation of themes**: Creating or identifying suitable themes based on the similarities and differences identified across the articles.
4. **Reviewing themes**: Ensuring that the proposed themes and subthemes are consistent with the main context of each article.
5. **Defining and naming themes**: Establishing three main themes and 28 subthemes based on the analysis of the selected articles.
6. **Producing the report**: Reporting the findings of the thematic analysis, which in this case refers to the SLR study.

3 Results

Table 3 shows the overall review collected 43 articles from 12 countries, including Indonesia, India, China, Pakistan, South Korea, the United Kingdom, Saudia Arabia, Jordan, the United States, France, Bangladesh, and the Czech Republic. This study produced 43 publications between 2019 and 2024: 5 in 2019, 1 in 2020, 7 in 2021, 14 in 2022, 13 in 2023, and 3 in 2024. The number of fake review detection studies from various countries from 2019 to 2024 was determined.

After conducting a thematic analysis, three primary themes and a total of 28 subthemes were identified and developed. The study presents the current implementation of the SA level used in fake review detection, organized into three subthemes (3 subthemes), the used methods or techniques for fake review detection (21 subthemes), and the imbalanced data handling techniques (4 subthemes). We presented the thematic analysis results in Figure 2, which shows the distribution of articles by main themes and subthemes.

Out of all the studies conducted, document-level SA had the highest number of articles (37). Regarding methods, Support Vector Machine (SVM) was the most commonly used (16 studies). As for the imbalanced data handling technique, resampling was the most effective (5 studies).

Based on these 43 articles, a quality assessment was conducted to evaluate the methodological rigor of the included studies. Following Kitchenham and Charters [18], a checklist was developed and tailored to the objectives of this study, focusing on sentiment analysis levels, methodological transparency, imbalanced dataset handling, and evaluation reporting. Each study was assessed using five criteria, with scores assigned as Yes (1), Partial (0.5), or No (0), as shown in Table 4, see Figure 2).

The quality assessment results in Table 5 indicate that most of the selected studies demonstrate moderate to high methodological quality. The majority achieved full scores for QA1 and QA5, showing that research objectives are clearly stated and evaluation metrics are consistently reported. In addition, many studies provide well-defined methodological descriptions (QA3), particularly those employing machine learning and deep learning approaches. This reflects a strong emphasis in the literature on model development and performance evaluation.

However, several important limitations are evident. Many studies only partially address QA2, as the level of sentiment analysis is often not explicitly specified, reducing clarity and comparability across studies. More critically, QA4 shows that only a limited number of studies consider class imbalance, despite its known impact on classification performance. This highlights a significant research gap, indicating the need for approaches that integrate fine-grained sentiment analysis with effective imbalanced dataset handling, which is the focus of this study.

Table 6 and Figure 3 illustrate the percentage distribution of the countries with the number of studies in each country. India is the leading country for published papers on fake review detection, with fourteen studies and articles. China follows second with ten articles, whereas Indonesia and the United States have four studies. South Korea and Bangladesh each have two studies. Additionally, one paper each is from Iraq, Pakistan, the United Kingdom, Saudi Arabia, Jordan, France and the Czech Republic.

Figure 4 presents a breakdown of the three primary themes across the 28 subthemes. Based on the analysis, SA level represented 11% (3 out of 28 articles for subthemes), methods accounted for 75% (21 out of 28 articles for subthemes), and imbalanced data handling techniques comprised 14% (4 out of 28 articles for subthemes). The findings suggest that researchers focus a significant proportion of their work on the methods employed in fake review detection.

4 Discussion

The primary goal of conducting an SLR is to examine the key factors involved in detecting fake reviews. The current analysis covered 43 papers that focused on three main themes: the level of SA, the methods used in fake review detection, and the techniques used to handle imbalanced data in fake review detection.

4.1 Sentiment Analysis Level Used in Fake Review Detection

SA has three levels: document, sentence, and aspect. Document level determines the sentiment expressed throughout a document [65]. On the other hand, sentence level focuses on analyzing the sentiment of individual sentences within a document [66]. Aspect-level SA delves deeper into specific aspects or features within the text to determine sentiment [67]. As shown in Figure

Table 3. Matrix Table on SLR Research Studies from 2019 to 2024.
Note: SA Level = Sentiment Analysis Level (DL = Document Level, SL = Sentence Level, AL = Aspect Level); RB = Rule-Based; SVM = Support Vector Machine; RF = Random Forest; LR = Logistic Regression; XGBOOST = Extreme Gradient Boosting; NB = Naïve Bayes; KNN = K-Nearest Neighbors; DT = Decision Tree; MNB = Multinomial Naïve Bayes; SVC = Support Vector Classifier; SGD = Stochastic Gradient Descent; BNB = Bernoulli Naïve Bayes; KMEANS = K-Means; GMM = Gaussian Mixture Model; LDA = Latent Dirichlet Allocation; CNN = Convolutional Neural Network; LSTM = Long Short-Term Memory; MLP = Multilayer Perceptron; BiLSTM = Bidirectional LSTM; RNN = Recurrent Neural Network; BERT = Bidirectional Encoder Representations from Transformers; IDHT = Imbalanced Data Handling Technique (Rp = Resampling, SMOTE = Synthetic Minority Over-sampling Technique, EM = Evaluation Metric, CMD = Collect More Data)

		SA Level			**Method**																					**IDHT**			
Author	**Country**	**DL**	**SL**	**AL**	**RB**	**SVM**	**RF**	**LR**	**XGBOOST**	**NB**	**KNN**	**DT**	**MNB**	**SVC**	**SGD**	**BNB**	**KMEANS**	**GMM**	**LDA**	**CNN**	**LSTM**	**MLP**	**BiLSTM**	**RNN**	**BERT**	**Rp**	**SMOTE**	**EM**	**CMD**
[24]	South Korea	✓				✓	✓	✓																					
[25]	United Kingdom	✓				✓																							
[26]	Indonesia	✓					✓	✓																					
[27]	India	✓				✓		✓																					
[28]	India	✓																		✓				✓					
[29]	India	✓						✓					✓																
[30]	India	✓				✓		✓					✓																
[31]	India	✓																		✓									
[32]	Pakistan	✓																		✓						✓			
[5]	Iraq	✓							✓	✓	✓																		
[33]	Indonesia	✓																		✓						✓			
[34]	South Korea	✓					✓	✓			✓			✓															✓
[35]	India	✓																		✓								✓	
[36]	Jordan	✓				✓		✓				✓																	
[37]	United States			✓																✓	✓								
[38]	India			✓																✓	✓								
[39]	China			✓					✓								✓						✓						
[40]	China	✓																		✓				✓					
[41]	India	✓																							✓				
[42]	United States	✓					✓	✓					✓			✓									✓			✓	
[43]	China	✓				✓	✓			✓																			
[44]	India	✓															✓	✓								✓			
[45]	China	✓																		✓			✓						
[46]	China	✓																	✓										
[47]	India	✓				✓	✓	✓		✓	✓	✓																	
[48]	India	✓					✓	✓	✓	✓		✓															✓		
[49]	Indonesia	✓				✓	✓	✓																					
[50]	France	✓																	✓										
[51]	India	✓			✓																								
[52]	Saudi Arabia	✓																		✓			✓						
[53]	Indonesia	✓																			✓								✓
[54]	India	✓				✓																							
[55]	United States	✓			✓	✓																							
[56]	China	✓																	✓				✓						
[1]	China			✓																✓	✓		✓						
[57]	India	✓					✓	✓																					
[58]	China	✓				✓	✓	✓			✓	✓														✓			
[59]	Bangladesh	✓				✓		✓		✓																			
[60]	Bangladesh	✓				✓			✓			✓			✓														
[61]	United States	✓				✓		✓	✓	✓																✓			
[62]	Czech Republic	✓				✓				✓																			
[63]	China			✓																		✓							
[64]	China			✓		✓											✓		✓										
Total		37	0	6	2	16	15	10	5	6	3	5	3	2	2	1	3	1	4	11	4	1	5	2	2	5	1	2	2

Table 4. Quality Assessment Checklist and Scoring Scheme

Code	Quality Assessment Question	Score
QA1	Is the research objective clearly stated?	1 / 0.5 / 0
QA2	Does the study clearly specify the level of sentiment analysis (e.g., document, sentence, aspect)?	1 / 0.5 / 0
QA3	Is the proposed method/model clearly described?	1 / 0.5 / 0
QA4	Does the study address class imbalance, and is the technique clearly described (e.g., SMOTE)?	1 / 0.5 / 0
QA5	Are evaluation metrics (e.g., accuracy, precision, recall, F1-score) clearly reported?	1 / 0.5 / 0

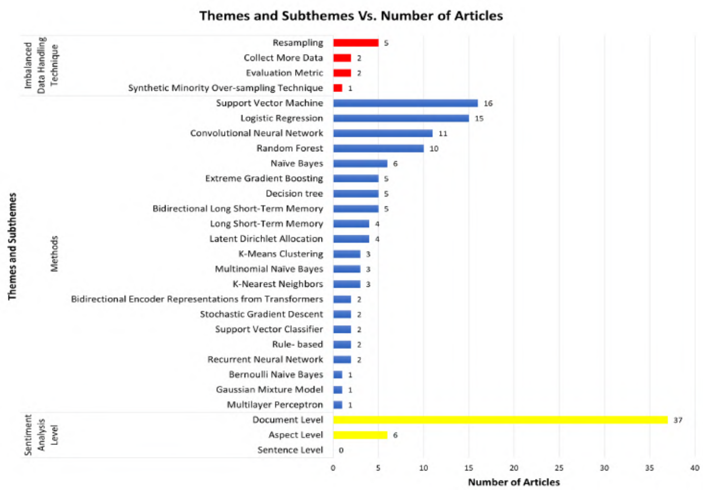

Figure 2. Themes and Subthemes Distributions based on Collected Articles

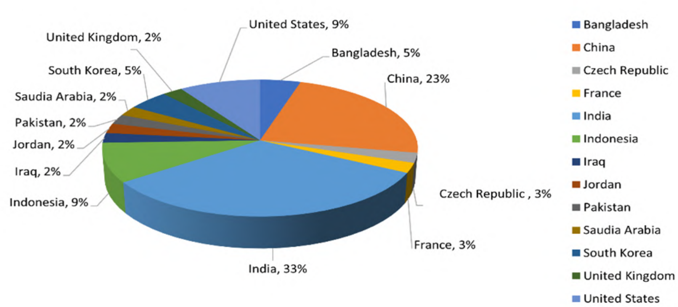

Figure 3. Percentage of Countries based on Reviewed Studies of Fake Review Detection

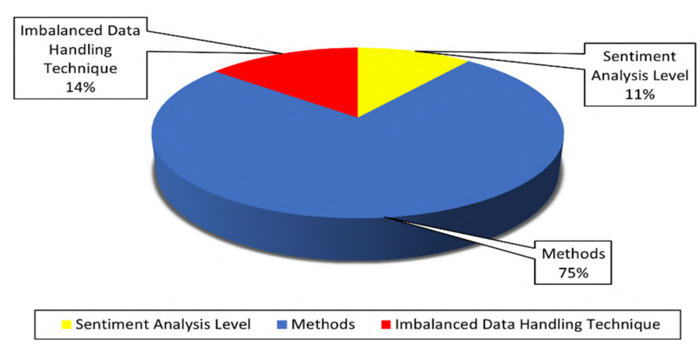

Figure 4. Summary Percentage of Major Themes Distribution

5, the highest percentage level of SA used in fake review detection is at the document level, which received 86%.

On the other hand, aspect-level SA is also used to detect fake reviews. Additionally, it focuses on predicting the sentiment polarities of sentences concerning given aspect categories [68]. This SA level is suitable for analyzing each product review aspect, making it significant in identifying the sentiments for products or services. Hence, document-level and aspect-level

Table 5. Quality Assessment Results of Included Studies

Study	QA1	QA2	QA3	QA4	QA5	Total	Quality
[24]	1	0.5	1	0	1	3.5	Medium
[25]	1	0.5	1	0.5	1	4.0	High
[26]	1	0.5	1	0	1	3.5	Medium
[27]	1	0.5	1	0	1	3.5	Medium
[28]	1	0.5	1	0	1	3.5	Medium
[29]	1	0.5	1	0	1	3.5	Medium
[30]	1	0.5	1	0	1	3.5	Medium
[31]	1	0.5	1	0	1	3.5	Medium
[32]	1	0.5	1	0	1	3.5	Medium
[5]	1	0.5	1	0	1	3.5	Medium
[33]	1	0.5	1	1	1	4.5	High
[34]	1	0.5	1	1	1	4.5	High
[35]	1	0.5	1	0	1	3.5	Medium
[36]	1	0.5	1	0	1	3.5	Medium
[37]	1	1	1	0	1	4.0	High
[38]	1	1	1	0	1	4.0	High
[39]	1	0.5	1	0.5	1	4.0	High
[40]	1	0.5	1	0	1	3.5	Medium
[41]	1	0.5	0	0	1	2.5	Medium
[42]	1	0.5	0.5	0	1	3.5	Medium
[43]	1	0.5	1	0.5	1	4.0	High
[44]	1	0.5	1	0	1	3.5	Medium
[45]	1	0.5	1	0	1	3.5	Medium
[46]	1	1	1	0	1	4.0	High
[47]	1	0.5	0.5	0	1	3.0	Medium
[48]	1	0.5	1	1	1	4.5	High
[49]	1	0.5	0.5	0	1	3.0	Medium
[50]	1	1	1	0	1	4.0	High
[51]	1	1	1	0	1	4.0	High
[52]	1	0.5	1	0	1	3.5	Medium
[53]	1	0.5	1	1	1	4.5	High
[54]	1	0.5	1	0	1	3.5	Medium
[55]	1	0.5	1	0	1	3.5	Medium
[56]	1	1	1	0	1	4.0	High
[1]	1	1	1	0	1	4.5	High
[57]	1	0.5	0.5	0	1	3.0	Medium
[58]	1	0.5	1	1	1	4.5	High
[59]	1	0.5	1	0	1	3.5	Medium
[60]	1	0.5	0.5	0	1	3.0	Medium
[61]	1	0.5	1	0	1	3.5	Medium
[62]	1	1	1	0	1	4.0	High
[63]	1	0.5	1	0	1	3.5	Medium
[64]	1	0.5	1	0	1	3.5	Medium

Table 6. Number of Studies in Each Country in Previous Research

Country	Number of Studies
India	14
China	10
Indonesia	4
United States	4
South Korea	2
Bangladesh	2
Czech Republic	1
France	1
Iraq	1
Jordan	1
Pakistan	1
Saudi Arabia	1
United Kingdom	1

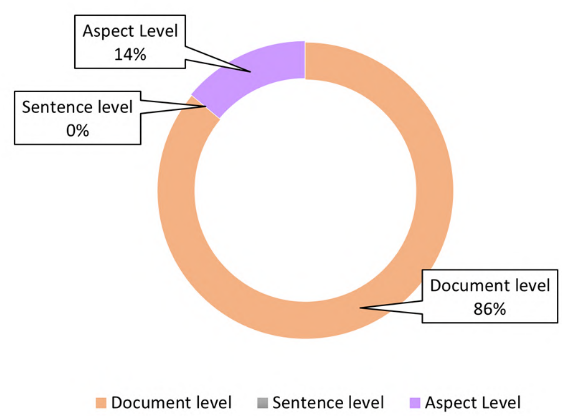

Figure 5. Percentage Level of Sentiment Analysis

are important levels that need to be used in detecting fake reviews so that the reviews can be understood and analyzed properly.

Table 7 and Figure 6 illustrate the distribution of SA levels applied in fake review detection studies sourced from two prominent academic databases, Scopus and WoS. We categorized the data across three primary levels: document level, sentence level, and aspect level. The analysis revealed that the document-level category is the most researched, with 37 studies identified in Scopus and 14 in WoS. Interestingly, the 14 articles in WoS are also available in Scopus, which means that the two databases overlap. This is due to the fact that, in the majority of cases, it promotes document-level SA implying that there is a tendency to analyze the overall sentiment of the review as opposed to the examination of certain elements of products or services.

On the other hand, the sentence level of research is still missing in both databases, which implies that no intensive study is conducted on individual sentences in reviews. Sentence-level SA may give an insight into subtle manifestations in a review. However, this method seems to be understudied in existing research on fake review detection.

It is possible that the lack of sentence-level in fake review detection studies can be explained by a number of practical and methodological issues. In contrast to document-level analysis, which summarizes the general feeling of a review, finer-grained annotation and text division is necessary in sentence-level SA, which makes data preprocessing and labelling more complicated. Moreover, bogus reviews tend to be based on minor and scattered false signals throughout the review, and sentence-level analysis is not as useful to recognize the overall deceptive intent.

On the modeling side, sentence-level SA can also create contextual information fragmentation that can decrease the performance of classification models that are based on holistic text patterns. Consequently, researchers tend to prioritize document-level or aspect-level approaches, which better capture contextual and semantic relationships within reviews. This highlights an opportunity for future research to explore hybrid approaches that integrate sentence-level insights with broader contextual analysis.

Table 7. The Distribution of Sentiment Analysis Levels based on Database

Sentiment Analysis Level	Database	Total
Document Level	Scopus	37
	WoS	14
Sentence Level	Scopus	0
	WoS	0
Aspect Level	Scopus	6
	WoS	4

The aspect level remains relatively underrepresented, though more researched than the sentence level, with six studies in Scopus, including the four studies also

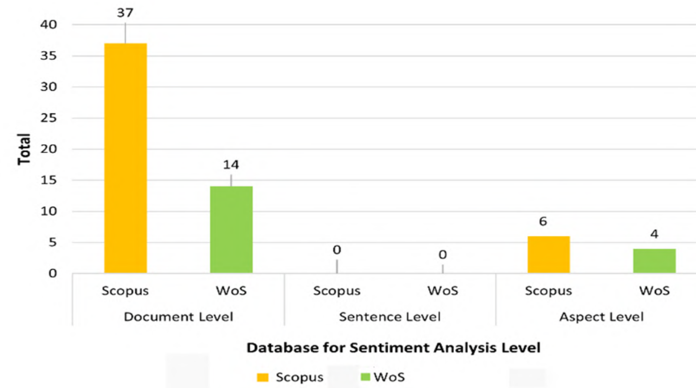

Figure 6. The Distribution of SA Levels based on Database

indexed in WoS. Aspect-level SA, which examines the sentiment associated with specific product or service attributes, could offer a more granular and precise understanding of fake reviews. This lower representation may indicate a research gap, as aspect-based analysis could enhance the detection of fake reviews by identifying inconsistencies in sentiment associated with different product features.

The findings indicate a strong preference for document-level analysis in fake review detection research, with limited application of aspect-level and sentence-level approaches. This suggests an opportunity for future studies to explore more detailed levels of sentiment analysis, particularly at the aspect level, to improve the accuracy and depth of fake review detection systems.

4.2 Methods Used in Fake Review Detection

Various ML algorithms, such as Rule-Based (RB), Support Vector Machine (SVM), Random Forest (RF), Logistic Regression (LR), Extreme Gradient Boosting (XGBOOST), Naïve Bayes (NB), K-Nearest Neighbors (KNN), Decision Tree (DT), Multinomial Naïve Bayes (MNB), Support Vector Classifier (SVC), Stochastic Gradient Descent (SGD), Bernoulli Naïve Bayes (BNB), K-Means Clustering (KMEANS), Gaussian Mixture Model (GMM), Latent Dirichlet Allocation (LDA), Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Multilayer Perceptron (MLP), Bidirectional Long Short-Term Memory (BiLSTM), Recurrent Neural Network (RNN), and Bidirectional Encoder Representations from Transformers

(BERT), have been used to detect fake reviews. SVM is the most widely used method for detecting fake reviews (14 studies), followed by LR (13 studies), according to Table 8 and Figure 7.

These methods have been employed in SA at the document level. SVM is preferred due to its effectiveness in accurately identifying fake reviews. The effectiveness of SVM in detecting fake reviews is underlined by [69]. They emphasize that when SVM is trained with appropriate lexicons and linguistic features, it can generate robust classification models for identifying fake reviews. Few studies have been done on detecting fake reviews at the aspect level compared to the document level. However, it is important to study the aspect level as it provides a more detailed and accurate sentiment analysis compared to traditional methods [70]. The aspect level analyses the aspects of products rather than the entire document. This results in a more precise sentiment for each aspect than for the whole review.

Aspect-based sentiment analysis (ABSA) is an aspect-level technique that can be defined as the type of SA in which attention is given to a task's specific aspect [7]. This SA technique determines the appropriate meaning of statements users wish to express regarding the product [71]. ABSA aims to identify a text sequence's complete and in-depth sentiment polarity towards a given aspect, usually in the form of explicitly mentioned aspect terms or implicit aspect categories [70].

However, the challenge of explicit ABSA is that it may miss out on implicit sentiments or hidden aspects not explicitly mentioned in the text, leading to incomplete SA [72]. The benefit of the implicit aspect compared to the explicit is that it can find the hidden meaning of the review, such as subtle opinions or implied attributes which are not directly mentioned in the text. Nevertheless, this must be done with more sophisticated methods, since it is necessary to find implicit items in terms of contextual and linguistic overtones. Such methods frequently involve deep learning models, such as BERT or LSTM, that are able to learn contextual connections in the text or hybrid methods that fuse NLP and ML to learn to determine implicit meanings in the text.

Transformer-based deep learning models, especially those that use transformers, have become a major trend in the field of fake review detection. Their features,

Table 8. The distribution of methods based on sentiment analysis level

Sentiment Analysis Level	Total	Method	Total
Document Level	37	Rule-Based	2
		SVM	14
		RF	10
		LR	15
		XGBOOST	4
		NB	6
		KNN	3
		DT	5
		MNB	3
		SVC	2
		SGD	2
		BNB	1
		K-MEANS	1
		GMM	1
		LDA	3
		CNN	9
		LSTM	1
		MLP	1
		BiLSTM	4
		RNN	4
		BERT	2
Aspect Level	6	SVM	1
		XGBOOST	1
		K-MEANS	2
		LDA	1
		CNN	3
		LSTM	3
		MLP	1

strengths, and weaknesses in relation to the traditional methods are explained in this subsection. In comparison to BERT, CNN, and LSTM, the three have shortcomings when it comes to context capturing. The CNNs also pay attention to local patterns and fail to capture larger contextual relations in text. LSTMs, though more adept at sequences, work on text in a unidirectional fashion, and important contextual nuances might be lost. Conversely, the bidirectional nature of BERT enables it to see the whole picture of a given word through information in both directions, thereby being more efficient in interpreting complex and nuanced language patterns [70]. Such a capability to understand the entire context makes BERT a better option in tasks such as implicit

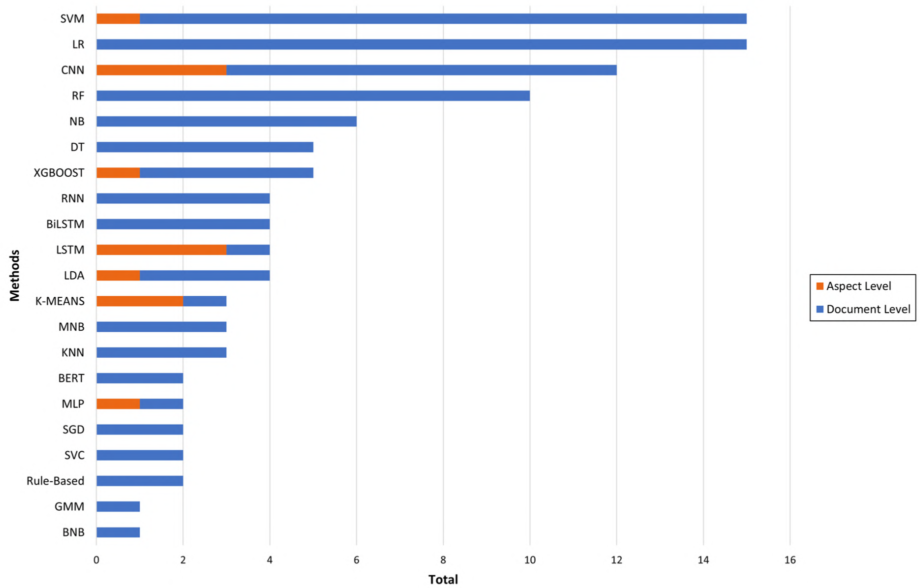

Figure 7. Methods Used based on Level of Sentiment Analysis

aspect extraction.

In the case of SVM, it is preferred in SA due to its speed, efficiency, and interpretability in contrast to other deep learning models, such as LSTM and CNN. Whereas deep learning models need large quantities of computational resources, and may be not transparent in large datasets, SVM provides superior accuracy and strength with smaller datasets [71] and [72] respectively. Its practicality and effectiveness make SVM the ideal choice for SA in implicit ABSA.

4.3 Imbalanced Data Handling Technique Used in Fake Review Detection

Various techniques were used to handle imbalanced data in fake review detection, including Resampling (Rp), Synthetic Minority Over-sampling Technique (SMOTE), Evaluation Metric (EM), and Collect More Data (CMD). Table 9 and Figure 8 display the distribution of imbalanced data handling techniques based on the SA level. Resampling is the most commonly used (5 studies) to improve accuracy and ensure fair results. Resampling techniques modify the number of instances in the majority and minority classes to create a more balanced dataset [12]. However, risks of overfitting or data loss are associated with their use.

Instead, SMOTE improves the quality of models by synthetically generating instances of the minority class,

Figure 8. Imbalanced Data Handling Techniques for Sentiment Analysis

producing a more balanced and diverse training set with none of such risks. Hence, SMOTE was chosen during this work to deal with the unequal datasets and enhance the precision and dependability of the fake review detecting systems. The fact that fake reviews usually constitute a minor portion of real-world data, makes SMOTE especially efficient in tackling the minority class problem. The creation of synthetic samples with the help of SMOTE helps balance the dataset and the model is better able to identify the fake reviews, improving the classification accuracy of the model in the process of identifying fake

Table 9. The Distribution of Imbalanced Data Handling Techniques based on Sentiment Analysis Level

Sentiment Analysis Level	Total	Imbalanced Data Handling Technique	Total
Document Level	37	Resampling (Rp)	5
		Evaluation Metric (EM)	2
		Collect More Data (CMD)	2
		Synthetic Minority Over-sampling Technique (SMOTE)	1

reviews better than otherwise would have been the case. Also, it is worth mentioning that research on the aspect level has not been conducted enough, such as skewed data processing methods in the fake review area. Table 10 and Figure 9 show the distribution of methods used to deal with imbalanced dataset in the study on fake review detection, published in two large databases, Scopus and WoS. The study highlights four primary techniques: Resampling, SMOTE, Evaluation Metrics, and Collecting More Data.

The most common of these methods is resampling, and there is a significant bias in the two databases in this regard. Five studies which use resampling are indexed in Scopus as well as four studies in WoS. The popularity of resampling is due to its simplicity and efficiency in responding to imbalanced data, namely in fake review detection. The SMOTE technique, which involves generating synthetic examples to balance minority classes, appears in only one Scopus study. Although SMOTE is a well-regarded method for handling imbalanced data, its limited use in this research area may suggest that researchers are either less familiar with it or consider it less suited to their specific datasets.

Evaluation metrics are also employed to handle class imbalance, particularly by setting performance criteria for data skewness. This approach appears in two studies in Scopus, including one indexed in WoS, indicating moderate usage. Evaluation Metrics indirectly manage imbalanced data by ensuring models are evaluated accurately despite the skewed data, rather than adjusting the data itself. Finally, more data were collected in only two studies indexed in Scopus and WoS. The time and resources required to increase the dataset manually may contribute to researchers' limited adoption.

Overall, the figure suggests a strong preference for resampling and evaluation metrics, with limited adoption of SMOTE and collecting more data. These findings highlight an area for further exploration, particularly in developing or applying more sophisticated data balancing techniques, such as SMOTE, to enhance the robustness of fake review detection systems.

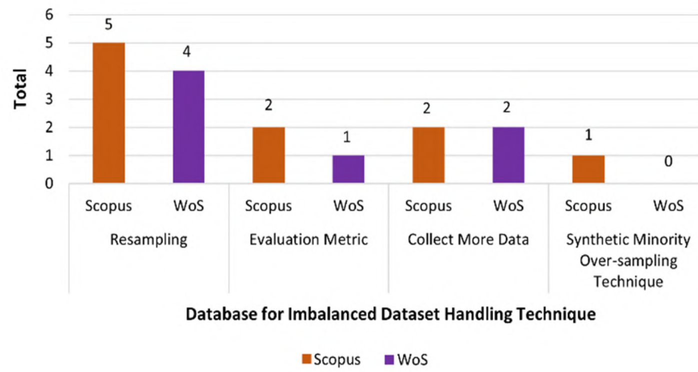

Figure 9. The Distribution of Imbalanced Dataset Handling Technique based on Database

4.4 Outcome from the Systematic Review

The main objective of this study is to conduct a systematic review of existing research on fake review detection, focusing on SA and imbalanced datasets. This review focuses on three primary themes: the level of SA applied in fake review detection, the methods and techniques used for detection, and the approaches to handling imbalanced data. The authors identified these themes through a systematic review of 43 articles, which they selected based on specific inclusion criteria focusing on studies from 2019 to 2024. The main databases used were Scopus and WoS.

The SLR identified three levels of sentiment analysis across the reviewed articles: document level, sentence level, and aspect level. Additionally, the analysis highlights the geographical distribution of research, with studies from 13 countries, including India, China, Indonesia, the United States, South Korea, Bangladesh,

Table 10. The distribution of imbalanced data handling techniques based on database

Imbalanced Data Handling Technique	Database	Total
Resampling	Scopus	5
	WoS	4
Evaluation Metric	Scopus	2
	WoS	1
Collect More Data	Scopus	2
	WoS	2
Synthetic Minority Over-sampling Technique	Scopus	1
	WoS	0

and the United Kingdom. However, the amount of research remains insufficient, as fake review detection requires SA and effectively handling imbalanced data. Thus, these themes often intersect within the studies.

This review aimed to address the gap in comprehensive research on sentiment analysis and imbalanced data handling in fake review detection, thus identifying 21 distinct methods. The methods are RB, SVM, RF, LR, XGBOOST, NB, KNN, DT, MNB, SVC, SGD, BNB, KMEANS, GMM, LDA, CNN, LSTM, MLP, BiLSTM, RNN, and BERT. Although researchers have used various algorithms to enhance fake review detection, most apply them at the document level, which may not suit detecting fake reviews on specific e-commerce products. Research on fake review detection at the aspect level remains limited. This underscores the need for more detailed, accurate sentiment analysis at this granularity.

This SLR also focuses on the imbalanced data handling techniques used in fake review detection, identifying four different techniques from the review. The techniques are Rp, SMOTE, EM, and CMD. The Rp technique modifies the dataset by adjusting the instances in the majority and minority classes. However, it can introduce risks of overfitting or data loss. CMD involves manually adding data to the dataset. This is a time-consuming and resource-intensive process. In contrast, SMOTE generates synthetic instances of the minority class to balance the dataset without these risks, often leading to improved model performance. Notably, research on aspect-level sentiment analysis incorporating imbalanced data handling techniques in fake review detection is lacking. This suggests an opportunity for further studies in this area.

In summary, this SLR has provided a comprehensive overview of current research in fake review detection, highlighting the primary sentiment analysis levels, methods, and imbalanced data handling techniques utilized in recent studies. While significant progress has been made, especially at the document level of sentiment analysis, the findings reveal gaps, particularly in applying aspect-level analysis and advanced data balancing techniques in fake review detection. The limited focus on aspect-level sentiment analysis suggests an opportunity for future research to explore more granular approaches, potentially enhancing accuracy in detecting nuanced review characteristics across e-commerce platforms. Additionally, effective imbalanced data handling methods remain critical, as balanced datasets are essential for model reliability and robustness. This review encourages further exploration and development of innovative methodologies to address these gaps, ultimately advancing the field of fake review detection and enhancing its applicability in real-world scenarios.

4.5 Research Gaps and Recommendations

The findings of this study have significant implications for enhancing the techniques used in fake review detection. These implications are important for researchers, data scientists, and developers of review platforms such as Amazon, as they highlight potential weaknesses that could decrease the precision and effectiveness of fake review detection. In addition, addressing these issues is crucial to enhancing the accuracy and reliability of systems designed to identify fake reviews. Even though the

SLR was conducted with meticulous attention to detail, certain limitations remain. Based on the findings of this study, future researchers are advised to investigate the following gaps:

- Most studies on fake review detection focus on sentiment analysis at the document level, with limited attention given to aspect-level analysis. Consequently, future research should explore aspect-level sentiment analysis more extensively to provide finer-grained insights into which specific aspects of a product or service are liked or disliked by consumers-insights that may be overlooked at the document level.
- Aspect-level sentiment analysis, which offers more detailed and precise sentiment interpretation, remains underrepresented in fake review detection research. Therefore, researchers should prioritize the development and application of aspect-level methods, such as Aspect-Based Sentiment Analysis (ABSA), to enable more accurate analysis of individual product or service attributes.
- There is a noticeable lack of studies addressing imbalanced data handling specifically within aspect-level sentiment analysis for fake review detection. Future work should investigate and propose effective imbalance-handling techniques at the aspect level to enhance classification accuracy and ensure fairer sentiment representation.

Most studies utilize a limited range of ML algorithms for fake review detection, primarily focusing on methods like CNN and SVM. Researchers should explore various ML algorithms, including advanced and hybrid approaches, to enhance the detection of fake reviews.

4.6 Research Contributions

This SLR offers an in-depth review of the existing practices in fake review detection with a special emphasis on the degree of SA, the way fake review detection methods and imbalanced data treatment. The review recognizes that there are important trends at different levels of SA, i.e. document, sentence, and aspect levels, and explores the detection methods used at each level, and whether imbalanced data handling techniques, e.g. SMOTE, resampling, gathering more data and evaluation metrics, have been used. The results indicate the most appropriate applications of SA, detection techniques that are widely used and existing approaches to address imbalanced datasets in this field. Compared to the previous reviews, which considered one of the two dimensions of SA methods or unbalanced data processing, the study is the first of its kind to take both dimensions into account, revealing some critical gaps, including the almost no coverage of the implicit components of ABSA and its use of unbalanced data processing methods to detect fake reviews.

This SLR results provide useful information to researchers, practitioners and system developers by proposing useful methods and pointing out future research directions to improve fake review detection systems. This review contributes greatly to the field of detecting fake reviews by offering a roadmap on how to enhance the accuracy, efficiency, and scalability of the SA and imbalanced data processing methods.

5 Conclusion

This study aims to conduct SLR focusing on the trends in SA and imbalanced data handling in fake review detection from 2019 to 2024. Employing the PRISMA approach and using thematic analysis, 43 papers were selected from Scopus and WoS. The study categorizes the research into three main themes: SA level, methods, and imbalanced data handling techniques. Within these themes, the study identified 28 subthemes, including SA level applied (11%), methods employed (75%), and imbalanced data handling techniques utilized (14%).

The SLR revealed that most research focused on document-level SA to detect fake reviews. However, fake reviews require aspect-level analysis to ensure that the sentiment of each aspect of the product is reviewed. Thus, it is recommended to use Aspect-Based SA, which is a process that involves detecting specific aspects of provided target entities, such as products or services and assessing the polarity, also known as the sentiment expressed towards each of these aspects, in terms of whether it is positive, negative, or neutral [14]. The methods used in the studies were primarily ML algorithms, such as SVM, limiting the enhancement of fake review detection. The techniques for handling imbalanced data were also analyzed, as they are commonly used in fake review detection research to increase classification accuracy. However, most studies focused on document-level analysis, lacking research on aspect-level analysis that combines with imbalanced data handling techniques. This is crucial to ensure that the results are fair, unbiased, and trustworthy.

In conclusion, the findings of this SLR hold significant potential for researchers, data scientists, and developers of review platforms by offering insights to enhance understanding and address issues associated with fake review detection. The implications extend to customers, business owners, and governments, contributing to the enhancement of fake review detection and improving the online environment for purchasing outcomes in the future.

Data Availability Statement

No new data were created or analyzed in this study. All data supporting the findings are derived from previously published articles, which are cited in the manuscript.

Author Contributions

Leena Ardini Abdul Rahim: Conceptualization, systematic review design, methodology, writing—original draft. **Khyrina Airin Fariza Abu Samah**: Conceptualization, methodology, supervision, validation, writing—reviewing and editing. **Mohamad Faiz Dzulkalnine**: Conceptualization, writing—reviewing and editing. **Ummu Mardhiah Abdul Jalil**: Data curation, literature screening, writing—reviewing and editing. **Mohd Nor Hajar Hasrol Jono**: Data curation, literature screening, validation, writing—reviewing and editing. **Nurul 'Azwa Kamarudin**: Validation, writing—reviewing and editing.

Compliance with Ethical Standards

It is declare that all authors don't have any conflict of interest. It is also declare that this article does not contain any studies with human participants or animals performed by any of the authors. Furthermore, informed consent was obtained from all individual participants included in the study.

AI Assistance Disclosure

The authors declare that the artificial intelligence (AI) tool Grammarly was used only for language editing, formatting, or technical refinement. No AI tool was used for the generation of research data, analysis, results, interpretations, or cited scholarly content. All AI-assisted content was reviewed and validated by the authors, who take full responsibility for the final manuscript.

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