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Leveraging Social Media Sentiment Analysis for Enhanced Disaster Management: A Systematic Review and Future Research Agenda

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Abstract. This systematic review examines the integration of sentiment analysis in disaster management, focusing on social media data analysis from 2018 to 2023. Through a rigorous selection process, six key studies were identified and analyzed, revealing significant advancements in sentiment classification techniques, including the application of deep learning models like Bidirectional Encoder Representations from Transformers (BERT) and Bidirectional Long Short-Term Memory (Bi-LSTM). This review synthesizes recent advancements in applying sentiment analysis to social media platforms, particularly twitter, to monitor and analyze public sentiment during disaster events. Moreover, the review highlights the predominance of negative sentiments during disasters and the potential of real-time sentiment analysis for enhancing disaster response strategies. However, persistent challenges in data quality, multilingual analysis, and ethical considerations were identified. The study contributes to the field by synthesizing current knowledge, identifying research gaps, and proposing future directions, including the development of more robust multilingual models and the integration of diverse data sources beyond Twitter. These findings have important implications for improving the effectiveness and responsiveness of disaster management practices through advanced sentiment analysis techniques.

Keywords: Sentiment analysis, social media platforms, Disaster management, information and communication technologies.

1. Introduction

A disaster is an unexpected, catastrophic event that severely disrupts a society or community, causing extensive human, economic, material, or environmental damage (Khan et al., 2021). These events can stem from both natural and human-made sources. Disasters alone can result in billions of dollars in losses and pose significant threats to human lives (Neelam & Sood, 2021). Consequently, numerous disasters worldwide, such as earthquakes and terrorist attacks, have led to substantial human casualties and economic damages. The importance of disaster management has risen among nations, prompting increased research in this field.

Disaster management involves handling the risks and challenges of disasters through continuous and strategic planning, using the help of researchers, disaster teams, affected people, and resources (Khan et al., 2021; Sumrit & Jongprasittiphol, 2024). Technology, especially information and communication technologies, can greatly improve health, education, and daily activities (Neelam & Sood, 2021). This approach has shaped disaster management, where these technologies are used to address disaster-related risks and challenges effectively. However, advances in and the growing importance of disaster management have led many nations to invest more in this field. As a result, there has been a significant increase in research publications in recent years (Wambrauw & Muttaqin, 2023).

Moreover, disaster management typically involves four phases: mitigation, preparedness, response, and recovery (Baxter et al., 2020). Government and non-government organizations frequently develop and occasionally work together on disaster preparedness and response plans (Phuyal et al., 2023). During the preparedness phase, logistical decisions are made to enhance the effectiveness of response and recovery operations. In the response and recovery phases, the delivery and accessibility of goods and services rely on the condition of the infrastructure and the capabilities of the supply chains.

In recent times, advancements in information and communication technology have significantly increased the volume of consumer feedback data available through online reviews (Mao et al., 2024; Muazu & Audi, 2021). This surge has made sentiment analysis a popular research topic (Kabir & Chowdhury, 2023). The field is increasingly recognized for its applications in real-world scenarios such as behavior analysis, decision-making, and deriving insightful information to foster organizational growth. Consequently, sentiment analysis offers a technological solution for understanding and interpreting consumer experiences, opinions, and behaviors on online platforms (Imran et al., 2015, Khan et al., 2023; Rodríguez-Ibánez et al., 2023). Despite the variability in the types of data used, the fundamental process flow for sentiment analysis remains consistent, as illustrated in Figure 1.

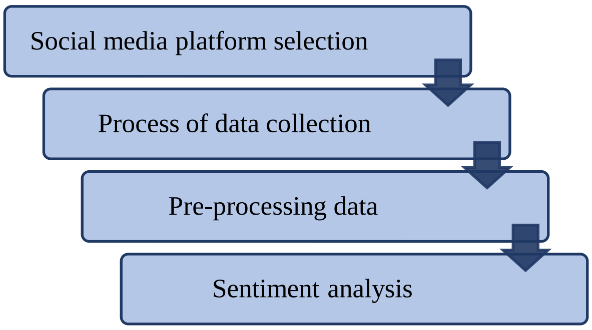

Fig. 1. Sentiment analysis process flow

A significant number of research papers have concentrated on the application of sentiment analysis using online reviews across a wide range of domains. In the financial sector, studies have explored how sentiment analysis can predict market trends (Cam et al., 2024; Fatouros et al., 2023). In education, researchers have utilized sentiment analysis to improve nursing education (Çiçek Korkmaz, 2023) and computer science education (Muazu et al., 2024). The tourism industry has benefited from sentiment analysis by understanding tourist preferences and enhancing service quality (H. Li et al., 2023). In the business domain, sentiment analysis has been applied to analyze consumer feedback and improve product offerings (Aakash et al., 2024). The healthcare sector has leveraged sentiment analysis to assess patient experiences and improve healthcare services on vaccination (Nurhaliza Agustina et al., 2024). Additionally, sentiment analysis has been used in government affairs to understand public opinion in the Chinese government (M. Li & Shi, 2023).

In recent years, have implemented sentiment analysis in disaster management. The landscape of disaster management has been significantly influenced by the widespread use of social media and online platforms, leading to a fundamental shift in how information is shared and processed during crises (Kryvasheyeu et al., 2016). These digital channels have become crucial sources of real-time data, offering unparalleled insights into public sentiment amidst disasters (Qu et al., 2023). Sentiment analysis, a subset of artificial intelligence that focuses on extracting and qualitatively evaluating subjective information from textual data, has emerged as a pivotal tool in disaster management (Ahmad et al., 2021; Hossain et al., 2023; Syed Zohaib et al., 2019). This computational technique enables the analysis of vast amounts of online content to discern public emotions and opinions, thereby providing valuable insights that can enhance disaster response efforts (Hassan et al., 2022; Kryvasheyeu et al., 2016). Despite the potential benefits of sentiment analysis in disaster management, its integration poses several challenges. These challenges include ensuring the accuracy of data, navigating the complexities of natural language processing, and addressing the ethical considerations surrounding data usage (Lee et al., 2020; Talia & Trunfio, 2023).

The objective of this paper is to review the current state of sentiment analysis within the realm of disaster management. Specifically, the paper aims to examine recent literature and uncover how sentiment analysis has been applied across different disaster scenarios. The goal is to present a comprehensive overview that synthesizes existing knowledge and identifies gaps and opportunities for future research in this field. Therefore, this review addresses three key questions:

1. How effective are current sentiment analysis techniques in analyzing disaster-related social media data?
2. What are the ethical considerations and challenges in using sentiment analysis for disaster management?
3. How can sentiment analysis be integrated into disaster response decision-making processes?

By addressing these questions, this review aims to provide a comprehensive understanding of the current state of sentiment analysis in disaster management and identify critical areas for future research.

The current study is organized into five sections. The first section provides the study's background. In the second section, the research methodology employed for the literature review is outlined. Section three is dedicated to analysis and findings. Section four delves into discussing the findings and suggesting future research directions. Lastly, the study's conclusion is presented in the fifth section.

2. Literature Review Methodology

The methodology for this literature review on sentiment analysis in disaster management involves a literature review approach adopted by (Rajeev et al., 2017). The primary goal is to provide a comprehensive overview of sentiment analysis techniques used in predicting disaster-related sentiment, explore ethical considerations in disaster management, and examine the integration of sentiment analysis into decision-making processes during disaster response and recovery phases. This methodology is crucial for identifying research gaps, positioning new research activities, and supporting evidence-based practices in disaster management.

2.1. Study Selection, Evaluation, and Review Process

In this study, we employ a literature review method to meticulously examine published research articles. This approach allows for creating a repeatable research plan, and the detailed documentation helps conduct a thorough analysis of research in a specific field (Rajeev et al., 2017). Additionally, a literature review can ensure accuracy and impartiality, allowing us to provide a comprehensive summary of current research and suggest future directions. As a result, previous review brought together literature on new areas like public service (Verma, 2022), social media security (Sharma & Jain, 2020), profit management (Firmansyah, 2023), higher education (Rajagukguk et al., 2023), and more. Moreover, the current study serves to consolidate and analyze the wealth of existing literature about different aspects of disaster management. By delving into various themes within this domain, it offers valuable insights for future researchers seeking to comprehend the evolution and intricacies of management practices, particularly disaster perspective.

The literature search was conducted across four major databases: ACM, IEEE, ScienceDirect, and Springer. We focused on papers published between 2018 and 2023 to capture the most recent developments in the field. The initial search yielded 87 papers, which were then screened based on relevance, resulting in a final selection of 6 papers for in-depth analysis. Based on the adopted process model, one specific search string was defined and delimited that is directly relevant to the research questions, and articles were collected based on that specific string. The search string used was "sentiment analysis in disaster management". Yet, the authors swiftly conducted a content check to gauge the quality and thoroughness of articles published across various journals or conferences, to determine the definitive set of papers for inclusion. Subsequently, in the last phase, papers specifically centered on disaster management issues were chosen for the study. A PRISMA flow diagram detailing this selection process is provided in Figure 2.

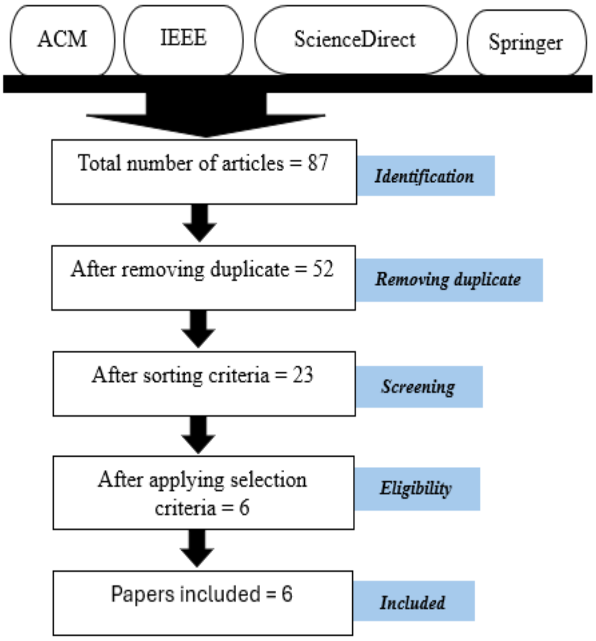

Fig. 2. A PRISMA flow diagram of the selection process

However, the selection criteria prioritized relevance, recency, and impact, ensuring the chosen papers were high quality and provided current insights into using sentiment analysis in disaster management. As a result, we omitted papers that solely addressed other domains such as supply chain management, profit management, health crisis management, and waste management. A content analysis of individual papers was conducted to select papers that specifically addressed the issues relevant to this study, with detailed information provided in Table 1.

Table 1. Stages involved in article selection for this study

Stage	Detail	Number of obtained records
Literature resources.	ACM, IEEE, ScienceDirect, and Springer.	4 databases.
Search strings	*Strings*: • Sentiment analysis in disaster management *Search space*: • Title. • Abstract. *Article type*: • Journal. • Conference. *Literature period*: • 2018. • 2019. • 2020. • 2021. • 2022. • 2023.	87 papers.
Sort criteria.	Articles must have standards of perceived quality relevance, and readability.	23 papers.
Selection criteria.	*Inclusion criteria*: • Articles addressing issues in disaster management such as distribution of sentiments, performance of sentiment analysis models, and implications for disaster management. *Exclusion criteria*: • Working papers. • Industrial reports. • Final year project reports. • Thesis reports. • Market reports. • News reports • Articles written not English language.	6 papers.

It's noticeable that this study encompasses several sequential stages within its review process. Firstly, a comprehensive literature search was conducted across databases to gather relevant papers on sentiment analysis in disaster management. Secondly, a two-stage screening process was employed to select primary studies that met the predefined inclusion criteria. Thirdly, data extraction was carried out using a standardized approach to collect information on study characteristics, sentiment analysis techniques, key findings, and implications from the chosen papers. Subsequently, the quality of selected studies was assessed based on predefined criteria to ensure the inclusion of studies meeting a minimum quality threshold, as detailed in Table 1. Finally, evidence synthesis involved summarizing findings, identifying common themes, and highlighting key insights related to sentiment analysis in disaster management using both qualitative and quantitative synthesis methods.

2.2. Reporting Findings

The review findings were documented in a structured format corresponding to each research question. Detailed summaries, supported by tables and figures where appropriate, illustrated key points and facilitated a clear understanding of the review outcomes. Conclusions drawn from the synthesized evidence provided insights into the effectiveness of sentiment analysis techniques, ethical considerations, and the integration of sentiment analysis in disaster management processes.

By following a rigorous methodology that integrates study selection, evaluation, and review processes, this review aims to provide a reliable and unbiased assessment of sentiment analysis in disaster management. The selected 6 high-quality papers from 2018 to 2023 will serve as a foundation for future research and practical applications in the field, contributing to the advancement of knowledge and evidence-based practices in disaster management.

3. Analysis and Findings

In this section, we analyze the findings from the literature review concerning sentiment analysis in disaster management. This analysis is structured following five sections: the distribution of sentiments, the performance of sentiment analysis models, the implications for disaster management, comparisons with previous studies, and methodological strengths and recommendations. Each section delves into specific aspects of how sentiment analysis has been utilized to understand public perception and improve disaster response strategies, providing a comprehensive overview of the current state of research in this field.

This study offers insights into how sentiment analysis related to disaster management has evolved, helping to contextualize the views of both the public and academics on the subject. By enhancing sentiment analysis, the research deepens our understanding of perceptions and reactions to disaster management practices within academic literature. Figure 3 illustrates the annual number of articles published on this topic from 2018 to 2023.

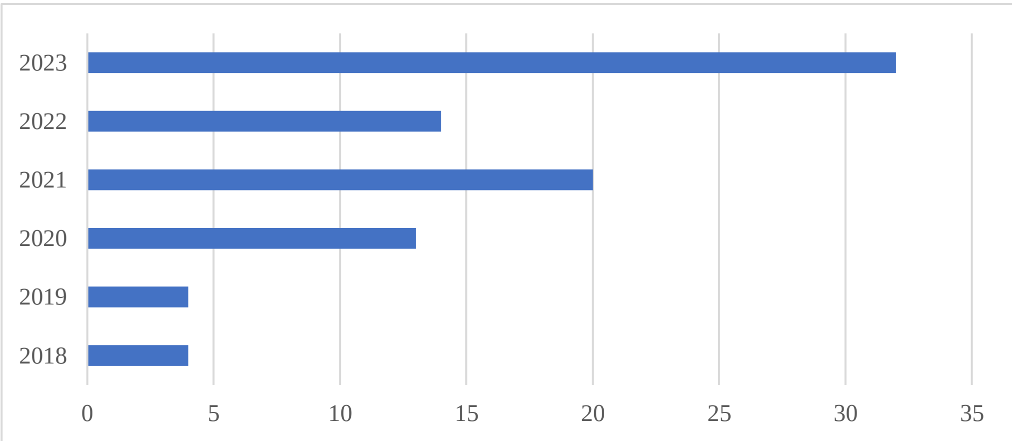

Fig. 3. Illustration of publication trend

Figure 3 illustrates the rise in the number of articles published on sentiment analysis in disaster management across four databases (ACM, IEEE, ScienceDirect, and Springer). From 2018 to 2023, a total of 87 articles were retrieved, with 2023 seeing the highest output at 32 articles. This trend suggests a growing interest and emphasis from the academic and research communities on sentiment analysis in disaster management. Your sentence has minor grammatical and typographical errors. Although out of the 87 articles retrieved, the IEEE database has the highest number of publications with 28 articles, followed by ScienceDirect with 25, Springer with 23, and ACM with 11 articles, as shown in Figure 4.

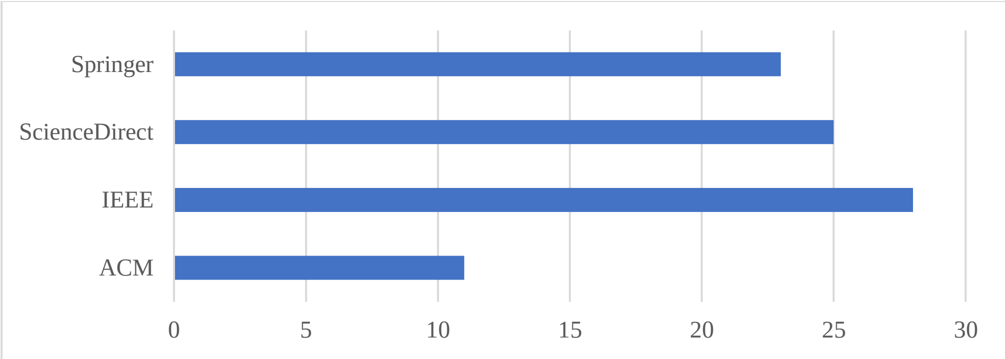

Fig. 4. Number of articles published in each database

3.1. Analysis of Sentiment Distribution

The study by (Saddam et al., 2023) aimed to analyze public sentiment regarding flood management in Jakarta through text mining and sentiment analysis. The researchers collected Twitter data related to the Jakarta floods and classified public opinion into positive, neutral, and negative categories. Results showed that 414 tweets had positive sentiments, while 2464 had negative sentiments. This sentiment distribution provides insights into the public's perception of flood management efforts in Jakarta. The study by (Ragini et al., 2018) revealed significant insights into public sentiment toward disaster management through the analysis of social media data. Tweets related to disasters were collected and categorized based on the needs of the affected people. The sentiment analysis classified these tweets into positive, neutral, and negative categories, providing a detailed distribution of public opinion. This sentiment distribution highlighted the areas where public satisfaction was high and where dissatisfaction prevailed, offering a clear picture of the public's perception of disaster response efforts.

The automated disaster monitoring system developed by (Sufi et al., 2023) effectively extracted location-oriented public sentiments from social media posts, specifically Twitter feeds. The system analyzed 67,528 tweets in 39 languages and successfully identified 9,727 location entities with over 70% confidence. The sentiment distribution revealed a nuanced understanding of public emotions during disaster events, categorized into positive, neutral, and negative sentiments. This comprehensive sentiment analysis provided a detailed view of public reactions and sentiments across different disaster situations, offering critical insights for disaster management. The study by (Melvin et al., 2023) analyzed sentiment distribution in social media posts related to disaster management, focusing on data from platforms such as Twitter and Facebook. The sentiment analysis categorized posts into positive, neutral, and negative sentiments, revealing a comprehensive picture of public emotions during disaster events. The analysis identified trends in sentiment distribution, showing that negative sentiments often dominate during disaster events, reflecting public concern and distress. This detailed sentiment distribution provides critical insights into public reaction and can inform disaster response strategies effectively.

The study by (Maharani, 2020) highlights the analysis of sentiment distribution during the Jakarta Flood in early 2020. Sentiments expressed in tweets were classified into positive, neutral, and negative categories. The findings revealed that a significant proportion of tweets expressed negative sentiments, reflecting public concern and dissatisfaction with the flood management efforts. This sentiment distribution provides critical insights into public perception and emotional responses during the disaster, which can inform emergency response strategies and improve communication with affected communities. The study conducted by (Choirul Rahmadan et al., 2020) analyzed sentiment distribution related to the Jakarta flood disaster using Twitter data. The sentiment analysis revealed that 79% of the tweets expressed negative sentiment, reflecting widespread public concern and dissatisfaction with the flood management efforts. This predominance of negative sentiment underscores the significant impact of the disaster on the affected population and highlights the critical areas needing attention from disaster management authorities.

3.2. Performance of Sentiment Analysis Models

(Saddam et al., 2023) used the classification method Support Vector Machine (SVM), a supervised learning method in machine learning. The model's performance was tested using the K-Fold Cross Validation method, resulting in an accuracy of 88.6%, precision of 88.6%, and recall of 89.4%. These metrics demonstrate the effectiveness of the SVM algorithm in sentiment classification for this study.

(Ragini et al., 2018) implemented various machine-learning algorithms to determine the most effective model for sentiment classification of disaster-related tweets. The study utilized features such as parts of speech and lexicons to enhance classification accuracy. The performance of these models was measured using standard metrics, with the Support Vector Machine (SVM) algorithm demonstrating high accuracy and reliability. The study's approach, including TF-IDF feature extraction and K-Fold cross-validation, ensured robust evaluation and validation of the models.

The performance of the sentiment analysis models in the study by (Sufi et al., 2023) was evaluated based on key metrics such as accuracy, precision, recall, and F1-Score. The system demonstrated high performance in monitoring various disaster types and extracting location entities. The combination of sentiment analysis, named entity recognition (NER), and anomaly detection algorithms ensured the accurate classification of sentiments and locations. The study's results showcased the system's robustness and reliability, highlighting its capability to process large volumes of multilingual social media data with high precision and accuracy.

(Melvin et al., 2023) evaluated various deep-learning models for sentiment analysis, including Bi-LSTM, CNN, and GRU. The experimental results demonstrated that Bi-LSTM outperformed other models, achieving accuracy levels of around 98%. This high performance underscores the effectiveness of deep learning models in processing and analyzing sentiment from social media data. The study also utilized traditional machine learning models such as KNN, SVM, and Naive Bayes for comparative analysis, reinforcing the superior performance of deep learning approaches in sentiment classification tasks.

(Maharani, 2020) evaluated the performance of various sentiment analysis models, including traditional machine learning methods like Support Vector Machines (SVM), Naive Bayes, and Random Forest, as well as advanced deep learning models such as CNN and BERT. The study found that the BERT method outperformed other models in classifying disaster-related tweets, particularly in capturing the context of language and handling the nuances of Indonesian tweets. Despite its superior performance, the study noted challenges in dealing with ambiguous and subjective tweets, indicating the need for further refinement of the model.

(Choirul Rahmadan et al., 2020) employed a lexicon-based approach for sentiment analysis and utilized the Latent Dirichlet Allocation (LDA) method for topic modeling. The lexicon-based approach proved effective in categorizing sentiments expressed in tweets, while the LDA method successfully identified and classified tweets into nine distinct topics. This combination of methods allowed for a detailed understanding of public sentiment and the key issues discussed during the disaster. However, the study acknowledges the need for improved data quality and handling of ambiguous and subjective tweets to enhance model performance.

3.3. Implications for Disaster Management

The findings of the study by (Saddam et al., 2023) underscore the potential utility of sentiment analysis in evaluating flood management in Jakarta. By capturing public opinion through sentiment analysis, policymakers and disaster management authorities can glean valuable insights into public sentiment, which can in turn inform decision-making and enhance flood management strategies.

The findings from (Ragini et al., 2018) carry significant implications for disaster management. By offering real-time categorization and classification of social media data, the proposed model can assist emergency responders in gaining insight into the immediate needs and sentiments of affected individuals. This real-time understanding can contribute to the development of more effective strategies for disaster response and recovery, ensuring efficient allocation of resources and timely support for those in need.

The real-time insights provided by the automated disaster monitoring system, as described by (Sufi et al., 2023) have significant implications for disaster management. By extracting location-oriented sentiments, the system enables emergency responders and policymakers to understand the public's needs and emotions during disaster events. This information can guide strategic decision-making and resource allocation, ensuring a more effective and timely response. The ability to monitor sentiments across different languages and regions enhances global situational awareness, supporting coordinated disaster management efforts.

The findings from (Melvin et al., 2023) have significant implications for disaster management. The ability to accurately analyze public sentiment during disasters helps identify potential dangers, develop preventive measures, and address the immediate needs of affected populations. By providing real-time insights into public emotions and concerns, sentiment analysis can enhance situational awareness and inform decision-making processes, leading to more effective disaster response and management strategies.

The implications of (Maharani, 2020) study for disaster management are substantial. By leveraging sentiment analysis of social media data, particularly Twitter, emergency responders, and policymakers can gain real-time insights into public sentiment and situational awareness. This information is crucial for identifying areas of immediate need, improving communication strategies, and deploying resources more effectively. The ability to classify and understand public sentiment during disasters can enhance overall disaster response efforts and contribute to more resilient disaster management practices.

The findings of (Choirul Rahmadan et al., 2020) have significant implications for disaster management. The high proportion of negative sentiments and the topics identified, such as feedback to the government and conditions during the disaster, provide valuable insights for emergency responders and policymakers. Understanding public sentiment and the key issues during a disaster can help in improving communication strategies, allocating resources more effectively, and addressing the specific needs and concerns of the affected population.

3.4. Comparison with Previous Studies

The literature review highlighted several studies utilizing sentiment analysis in various contexts, such as Islamophobia, COVID-19 outbreaks, and disaster management. For example, (Gata & Bayhaqy, 2020) conducted sentiment analysis related to Islamophobia using Naive Bayes and SVM algorithms. Syahputra et al. found that the SVM algorithm achieved higher accuracy compared to Naive Bayes. (Hussein et al., 2021) used K-means clustering for sentiment analysis of the COVID-19 outbreak. These comparisons underscore the versatility and effectiveness of sentiment analysis across different domains.

The literature review highlights the application of sentiment analysis across various disaster scenarios, including the Haiti earthquake and Hurricane Sandy. Previous studies have underscored the value of social media as both an early warning system and a means to understand public sentiment during crises. Building upon these findings, (Ragini et al., 2018) offer a more detailed categorization of needs and a rigorous evaluation of machine learning models for sentiment classification. In contrast to earlier research, the utilization of SVM and the emphasis on real-time analysis signify advancements in the application of sentiment analysis for disaster management.

(Sufi et al., 2023) compared their system's performance with existing disaster monitoring methods. Previous studies often faced limitations such as restricted language support, limited disaster-type monitoring, and lower accuracy in identifying disaster locations. In contrast, the proposed system addressed these challenges by processing tweets in 39 languages and achieving high accuracy in sentiment and location extraction. The study's comprehensive approach, including real-time data processing and mobile platform support, represents a significant advancement over earlier methods.

Compared to previous studies, (Melvin et al., 2023) highlighted the advancements in sentiment analysis techniques, particularly the use of deep learning models. Earlier research often relied on traditional machine learning approaches, which showed lower accuracy levels. The inclusion of Bi-LSTM and other deep learning models in the current study resulted in higher accuracy and more reliable sentiment classification. Additionally, the study's comprehensive approach, involving large-scale data collection and multi-language processing, represents a significant improvement over previous methodology.

Compared to previous studies, (Maharani, 2020) provides a more focused analysis of the use of BERT for sentiment analysis in disaster scenarios. While earlier research often relied on frequency-based and traditional machine learning methods, this study highlights the advantages of using advanced deep learning models. The BERT method demonstrated higher accuracy and a better understanding of context, which is essential for accurately classifying sentiment in disaster-related tweets. This represents a significant advancement over previous methodologies, which often struggled with the complexity and variability of social media data.

Compared to previous studies, the research by (Choirul Rahmadan et al., 2020) offers a more focused analysis of sentiment and topic modeling using the LDA method during a specific disaster event. While earlier research often utilized frequency-based and traditional machine learning methods, this study highlights the advantages of using advanced topic modeling techniques to analyze large-scale social media data. The integration of sentiment analysis with LDA provided a comprehensive view of public sentiment and the topics of concern, representing a significant advancement over previous methodologies.

3.5. Methodological Strengths and Recommendations

The research methodology implemented by (Saddam et al., 2023) included several stages: data collection, preprocessing, sentiment labeling, SVM implementation, model evaluation, and feature extraction using the TF-IDF technique. The study demonstrates the effectiveness of employing SVM and TF-IDF feature extraction in capturing public opinion. Additionally, it emphasizes the importance of enhancing accuracy for future research endeavors, suggesting the exploration of alternative algorithms and feature extraction techniques to improve sentiment analysis performance.

The methodology employed by (Ragini et al., 2018) was comprehensive, encompassing data collection from social networks, preprocessing, sentiment labeling, and machine learning implementation. The utilization of TF-IDF for feature extraction and K-Fold cross-validation for model evaluation were notable strengths. However, the study also highlighted challenges, such as the difficulty in acquiring disaster-related data and the absence of standardized crisis datasets.

The methodological strengths of the study by (Sufi et al., 2023) include the integration of advanced AI and NLP algorithms, such as sentiment analysis, NER, and anomaly detection, to process social media data. The use of APIs for sensing major disaster events and the deployment of a multi-language processing capability further enhanced the system's effectiveness. Recommendations for future research include expanding the dataset to include more social media platforms, developing standard crisis datasets, and refining the algorithms to improve accuracy and precision in sentiment and location extraction.

The methodological strengths of the study by (Melvin et al. 2023) include the use of advanced AI and NLP techniques, such as Bi-LSTM, for sentiment analysis. The study's rigorous approach to data collection, preprocessing, and model evaluation ensured high accuracy and reliability of the results. Recommendations for future research include expanding the dataset to include more social media platforms, enhancing multi-language support, and continuously updating the models to maintain high performance. Additionally, developing standard disaster-related lexicons and improving data collection techniques can further enhance the effectiveness of sentiment analysis in disaster management.

The methodological strengths of the study by (Maharani, 2020) include the implementation of BERT, a state-of-the-art NLP model, and the comprehensive analysis of sentiment distribution in disaster-related tweets. The study's robust data preprocessing and model evaluation processes ensured the high accuracy and reliability of the results. Recommendations for future research include improving data quality, enhancing the handling of ambiguity and subjectivity in tweets, and expanding the dataset to include more diverse sources of social media data. Additionally, integrating sentiment analysis with other data sources, such as news reports and official announcements, could further improve situational awareness and disaster response efforts.

The methodological strengths of (Choirul Rahmadan et al., 2020) include the use of Twitter's API for data collection, robust data preprocessing, and the application of both sentiment analysis and topic modeling. The study's comprehensive approach ensured high accuracy in sentiment classification and topic identification. Recommendations for future research include improving data quality, enhancing the handling of ambiguous and subjective tweets, and exploring other advanced topic modeling techniques to achieve better results. Additionally, integrating sentiment analysis with geolocation data could provide more granular insights into the affected areas and the specific needs of those regions.

Table 2. Comparisons between the findings of the literature studies

Study	Sentiment Distribution	Performance of Sentiment Analysis Models	Implications for Disaster Management	Comparison with Previous Studies	Methodological Strengths and Recommendations
Saddam et al., 2023	414 positive, 2464 negative tweets on Jakarta floods.	SVM with K-Fold Cross Validation. Accuracy: 88.6%, Precision: 88.6%, Recall: 89.4%.	Captures public opinion on flood management. Can inform policy decisions and improve strategies.	Highlights the versatility of sentiment analysis, compared to studies on Islamophobia and COVID-19. Demonstrates SVM's effectiveness.	Effective use of SVM and TF-IDF. Recommends exploring alternative algorithms and feature extraction techniques for better performance.
Ragini et al., 2018	Not specified	SVM with TF-IDF feature extraction. High accuracy and reliability.	Real-time insights into affected individuals' needs and sentiments, aiding efficient resource allocation and timely support.	Advanced categorization of needs and rigorous model evaluation, compared to studies on Haiti earthquake and Hurricane Sandy.	Comprehensive methodology including TF-IDF and K-Fold cross-validation. Highlights challenges in data acquisition and lack of standardized crisis datasets.
Sufi et al., 2023	67,528 tweets analysed in 39 languages, identifying 9,727 location entities.	High performance in accuracy, precision, recall, and F1-Score.	Real-time, location-oriented sentiments guide strategic decision-making	Comprehensive approach with multi-language support and high accuracy, surpassing	Integration of AI and NLP algorithms. Recommends expanding dataset, developing

		Combination of sentiment analysis, NER, and anomaly detection.	and resource allocation. Enhances global situational awareness.	limitations of previous studies.	standard crisis datasets, and refining algorithms for better accuracy and precision.
Melvin et al. 2023	Negative sentiments often dominate during disaster events.	Evaluated deep-learning models (Bi-LSTM, CNN, GRU). Bi-LSTM achieved ~98% accuracy. Compared with traditional models like KNN, SVM, Naive Bayes.	Enhances situational awareness and decision-making.	Advanced use of deep learning models (Bi-LSTM) compared to traditional approaches, resulting in higher accuracy and reliable sentiment classification.	Use of advanced AI and NLP techniques (Bi-LSTM). Recommends expanding dataset, enhancing multi-language support, developing disaster-related lexicons, and improving data collection.
Maharani, 2020	Showed significant negative sentiments.	Evaluated SVM, Naive Bayes, Random Forest, CNN, and BERT.	Improves communication strategies and resource deployment.	Focused on BERT for sentiment analysis in disaster scenarios, demonstrating higher accuracy and better context understanding compared to previous methods.	Implementation of BERT for sentiment analysis. Recommends improving data quality, handling ambiguity and subjectivity in tweets, expanding dataset, and integrating other data sources for better situational awareness.
Choirul Rahmadan et al., 2020	79% negative sentiment in tweets on Jakarta flood.	Lexicon-based approach for sentiment analysis and LDA for topic modelling.	High negative sentiment and identified topics provide valuable insights for improving communication, resource allocation, and addressing public needs.	Combined sentiment analysis with topic modelling (LDA), providing a comprehensive view of public sentiment and key issues, surpassing previous methodologies.	Use of Twitter's API, robust data preprocessing, sentiment analysis, and topic modeling. Recommends improving data quality, handling ambiguous tweets, exploring advanced topic modeling techniques, and integrating geolocation data for more granular insights.

Table 2 provide the analysis of the six literature studies which reveals that sentiment analysis of social media data, particularly from Twitter, offers valuable insights into public sentiment during disaster events. Studies consistently found a predominance of negative sentiments, reflecting public dissatisfaction and concern, particularly in flood management scenarios in Jakarta. Various machine learning and deep learning models, including SVM, Bi-LSTM, and BERT, were employed, demonstrating high accuracy and reliability in sentiment classification. These methodologies highlight the importance of real-time, nuanced sentiment analysis for improving disaster response strategies, resource allocation, and communication with affected communities. Moreover, integrating advanced AI and NLP techniques, multi-language processing, and real-time data analysis significantly enhances the effectiveness of disaster management efforts. Future research should focus on refining models, expanding datasets, and integrating additional data sources to further improve situational awareness and response capabilities.

In summary, this research provides an in-depth analysis of sentiment distribution, model performance, implications for disaster management, comparisons with previous studies, and methodological strengths and recommendations. The findings underscore the importance of sentiment analysis in understanding public perceptions and improving disaster response strategies. By leveraging advanced sentiment analysis techniques, researchers and policymakers can enhance their ability to manage disasters more effectively, ensuring timely and appropriate responses to public needs and concerns.

4. Discussion

This section synthesizes the findings from various studies exploring sentiment analysis in the context of disaster management. By employing different methodologies and leveraging social media data, these studies provide a comprehensive understanding of public sentiment and its implications for disaster management. The key studies discussed include those by (Saddam et al., 2023), (Ragini et al., 2018), (Sufi et al., 2023), (Melvin et al., 2023), (Maharani, 2020), and (Choirul Rahmadan et al., 2020). The chapter is structured into four main sections: synthesis of findings, interpretation and analysis, methodological reflections, and practical implications and recommendations. It concludes with a discussion of future research directions, highlighting potential advancements in this field.

4.1. Synthesis of Findings

(Saddam et al., 2023) conducted a sentiment analysis of flood disaster management in Jakarta revealing significant insights into public opinion as expressed on Twitter. By employing the Support Vector Machine (SVM) algorithm, the study successfully categorized tweets into positive, neutral, and negative sentiments. The analysis showed a predominance of negative sentiment, with 2464 tweets classified as negative and 414 as positive. The performance metrics, including an accuracy of 88.6%, precision of 88.6%, and recall of 89.4%, highlighted the robustness of the SVM model in sentiment classification. These findings indicate a general dissatisfaction among the public regarding flood management in Jakarta.

The study investigated the application of sentiment analysis to disaster management by analyzing social media data, specifically tweets related to flood disasters in Jakarta (Ragini et al., 2018). Using the Support Vector Machine (SVM) algorithm, the research effectively categorized tweets into positive, neutral, and negative sentiments, revealing a predominance of negative sentiment regarding flood management. The performance metrics demonstrated high accuracy, precision, and recall, indicating the model's effectiveness in sentiment classification. The analysis provided valuable insights into public opinion, highlighting areas of dissatisfaction and potential improvements in disaster response strategies.

The study by (Sufi et al., 2023) presented a novel automated disaster monitoring system that leverages AI and NLP to extract location-oriented public sentiments from social media posts. The system processed a substantial volume of tweets in multiple languages, demonstrating high accuracy and precision in monitoring various disaster types. The real-time insights provided by the system offer valuable support for strategic decision-makers and policymakers, addressing the limitations of existing disaster monitoring methods and enhancing situational awareness.

The study by (Melvin et al., 2023) demonstrated the potential of sentiment analysis in disaster management by leveraging advanced deep-learning models to analyze social media posts. The results showed that Bi-LSTM models achieved high accuracy in sentiment classification, providing valuable insights into public sentiment during disaster events. The study's comprehensive approach to data collection and preprocessing, combined with advanced NLP techniques, highlighted the effectiveness of sentiment analysis in enhancing situational awareness and informing disaster response strategies.

(Maharani, 2020) presents a comprehensive study on the implementation of BERT for sentiment analysis during the Jakarta Flood. The findings indicate that BERT outperformed other models in accurately classifying sentiment in disaster-related tweets. The analysis revealed that negative sentiments were predominant, reflecting public concern and dissatisfaction with the flood management efforts. The study underscores the potential of social media data as a valuable source of real-time information for disaster management and emergency response.

The study by (Choirul Rahmadan et al., 2020) presents a thorough analysis of sentiment and topics related to the Jakarta flood disaster using Twitter data. The findings revealed that the majority of tweets expressed negative sentiment, with key topics including information about flooded areas, the impact of the disaster, and feedback to the government. The use of the LDA method for topic modeling provided detailed insights into the public's concerns and issues during the disaster.

4.2. Interpretation and Analysis

The prevalence of negative sentiment, as highlighted by (Saddam et al., 2023), indicates widespread public concern and dissatisfaction with flood management practices in Jakarta. This negative perception likely arises from the frequent and severe impact of floods in the region, leading to significant displacement and disruption. Conversely, the comparatively lower occurrence of positive sentiments suggests a limited recognition of effective flood management measures. The demonstrated accuracy and reliability of the SVM model, as evidenced by the performance metrics, affirms its suitability for sentiment analysis in this context. Such analysis provides a clear depiction of public sentiment, which is crucial for understanding both the effectiveness and public perception of disaster management efforts.

(Ragini et al., 2018) observed a prevalence of negative sentiment in the tweets, indicating considerable public concern and dissatisfaction with current flood management practices in Jakarta. This negative perception likely stems from the frequent and severe impacts of floods in the region, resulting in significant displacement and disruption. The strong performance of the SVM model reinforces its suitability for sentiment analysis in this context, adeptly capturing the subtleties of public sentiment. Such analysis provides a comprehensive insight into public opinion, essential for assessing the effectiveness of disaster management efforts and pinpointing areas for enhancement.

(Sufi et al., 2023) demonstrate that the system's high performance in extracting and analyzing sentiments indicates its potential to significantly enhance disaster response and management. The real-time monitoring of public sentiment enables a more responsive and informed approach to disaster management. Analysis of sentiment distribution reveals key areas of public concern and satisfaction, providing actionable insights for emergency responders and policymakers. Moreover, the system's capability to process multilingual data ensures comprehensive monitoring of global disaster situations.

The high performance of the Bi-LSTM model in sentiment analysis indicates its potential as a powerful tool for disaster management (Melvin et al., 2023). The detailed sentiment distribution analysis revealed predominant negative sentiments during disasters, reflecting public concern and distress. These insights can guide emergency responders and policymakers in addressing the needs and concerns of affected populations more effectively. The study also highlighted the importance of using advanced NLP techniques to process and analyze large volumes of social media data accurately.

The high performance of the BERT model in (Maharani, 2020) study highlights its effectiveness in capturing the context and nuances of language in social media posts. The predominance of negative sentiments indicates a need for improved disaster management and communication strategies. The study's findings suggest that real-time sentiment analysis can provide valuable insights into public emotions and needs during disasters, enabling more responsive and effective emergency management.

The high proportion of negative sentiments identified by (Choirul Rahmadan et al., 2020) highlights the significant impact of the flood disaster on the public. The detailed topic modeling revealed specific areas of concern, such as the conditions during the disaster and the public's feedback to the government. These insights can help disaster management authorities understand the public's needs and improve their response strategies. The study's methodology, combining sentiment analysis with topic modeling, proved effective in capturing the complexity of public sentiment and the key issues discussed during the disaster.

4.3. Methodological Reflections

The methodology employed by (Saddam et al., 2023), involving data collection from Twitter, preprocessing, sentiment labeling, SVM implementation, and TF-IDF feature extraction, was systematically designed to ensure comprehensive sentiment analysis. The inclusion of K-Fold Cross Validation for model evaluation added robustness to the performance metrics. However, it's worth noting that the reliance on Twitter data may constrain the generalizability of the findings, as it represents the opinions of Twitter users, who may not be fully representative of the entire population. Additionally, the manual labeling of sentiments could potentially introduce bias. Despite these limitations, the methodological approach effectively captured public sentiment, showcasing the utility of SVM and TF-IDF in sentiment analysis.

The study's methodology, as conducted by (Ragini et al., 2018), was meticulously designed, encompassing several stages: data collection from Twitter, preprocessing, sentiment labeling, SVM implementation, and feature extraction using TF-IDF. The incorporation of K-Fold Cross Validation for model evaluation added robustness to the findings. However, it's important to note that the reliance on Twitter data may constrain the generalizability of the results, as it represents the opinions of Twitter users, who may not be fully representative of the entire population. Additionally, the manual labeling of sentiments could potentially introduce bias. Despite these limitations, the methodological approach effectively captured public sentiment, demonstrating the utility of SVM and TF-IDF in sentiment analysis for disaster management.

The study's methodology, which incorporated advanced AI and NLP techniques, demonstrated effectiveness in extracting and analyzing disaster-related sentiments (Sufi et al., 2023). The integration of sentiment analysis, Named Entity Recognition (NER), and anomaly detection algorithms provided a robust framework for processing social media data. However, the study also underscored challenges such as the necessity for standard crisis datasets and the difficulty in gathering disaster-related data from diverse sources. Addressing these challenges can further enhance the reliability and applicability of the system.

(Melvin et al., 2023) employed a robust methodological framework, incorporating advanced AI and NLP techniques for sentiment analysis. The use of deep learning models such as Bi-LSTM, CNN, and GRU demonstrated high accuracy and precision in sentiment classification. However, the study also acknowledged challenges such as the need for standard crisis datasets and the difficulty in collecting disaster-related data from diverse sources. Addressing these challenges can further enhance the system's reliability and applicability in real-world disaster scenarios.

(Maharani, 2020) employed a robust methodological framework, utilizing advanced NLP techniques to analyze sentiment in disaster-related tweets. The study's use of BERT, along with comprehensive data preprocessing and evaluation, ensured high accuracy in sentiment classification. However, challenges remain in handling ambiguous and subjective tweets. Future research should focus on enhancing model performance and addressing these challenges to improve the reliability and applicability of sentiment analysis in disaster scenarios.

(Choirul Rahmadan et al., 2020) employed a robust methodological framework, utilizing Twitter's API for data collection, a lexicon-based approach for sentiment analysis, and the LDA method for topic modeling. This comprehensive approach ensured high accuracy in sentiment classification and topic identification. However, challenges remain in handling ambiguous and subjective tweets. Future research should focus on enhancing model performance and addressing these challenges to improve the reliability and applicability of sentiment analysis in disaster scenarios.

4.4. Practical Implications and Recommendations

The insights gleaned from (Saddam et al., 2023) study bear significant implications for disaster management in Jakarta. The prevalence of negative sentiment underscores the urgency for enhanced flood management strategies. Policymakers and disaster management authorities should heed these public opinions to address concerns and bolster the efficacy of their measures. Leveraging social media platforms to engage with the public can offer real-time feedback and foster improved communication and trust. It is advisable to integrate sentiment analysis into the disaster management framework to continually monitor and assess public sentiment, enabling more agile and adaptive strategies.

The insights derived from this study carry significant implications for disaster management in Jakarta and similar contexts, as highlighted by (Ragini et al., 2018). The prevalence of negative sentiment underscores the necessity for enhanced flood management strategies. Policymakers and disaster management authorities should take into account these public opinions to address concerns and improve the efficacy of their measures. Engaging with the public through social media platforms can offer real-time feedback and promote better communication and trust. It is advisable to integrate sentiment analysis into the disaster management framework to continually monitor and assess public sentiment. This integration facilitates the development of more responsive and adaptive strategies, ensuring a proactive approach to disaster management.

The practical implications of the study by (Sufi et al., 2023) are substantial. The system's ability to provide real-time, location-oriented sentiment analysis can significantly enhance disaster response strategies. Policymakers and emergency responders can use these insights to allocate resources more effectively and address public concerns promptly. The availability of the system on mobile platforms ensures easy access and visualization of disaster insights. Recommendations for practical implementation include the integration of the system into existing disaster management frameworks and the continuous updating of algorithms to maintain high performance.

The practical implications of the study by (Melvin et al., 2023) are substantial. The ability to provide real-time sentiment analysis of social media posts can significantly enhance disaster response strategies. Policymakers and emergency responders can use these insights to allocate resources more effectively and address public concerns promptly. The study recommends integrating sentiment analysis into existing disaster management frameworks and continuously updating the models to maintain high performance. Additionally, developing user-friendly visualization tools, such as dashboards and maps, can facilitate the practical application of sentiment analysis in disaster response.

The practical implications of (Maharani, 2020) study are significant for disaster management. The ability to analyze and classify sentiment in real time provides critical insights for emergency responders and policymakers. The study recommends integrating sentiment analysis into existing disaster management frameworks, improving data quality, and continuously refining models to maintain high performance. Developing user-friendly visualization tools, such as dashboards and maps, can facilitate the practical application of sentiment analysis in disaster response and enhance situational awareness.

The practical implications of (Choirul Rahmadan et al., 2020) are significant for disaster management. The ability to analyze and classify sentiment in real time provides critical insights for emergency responders and policymakers. The study recommends integrating sentiment analysis into existing disaster management frameworks, improving data quality, and continuously refining models to maintain high performance. Developing user-friendly visualization tools, such as dashboards and maps, can facilitate the practical application of sentiment analysis in disaster response and enhance situational awareness.

4.5. Future Research Direction

(Saddam et al., 2023) future research endeavors should prioritize enhancing the accuracy and comprehensiveness of sentiment analysis in disaster management. Exploring additional algorithms, particularly deep learning models, holds promise for improving classification performance. Broadening the scope of data sources beyond Twitter to encompass other social media platforms and public forums would provide a more comprehensive understanding of public sentiment. Delving into the underlying reasons for negative sentiments through qualitative analysis could yield deeper insights into public concerns. Furthermore, conducting longitudinal studies to track sentiment changes over time could facilitate the assessment of the impact of policy interventions and improvements in disaster management strategies.

(Ragini et al., 2018) suggest that future research should prioritize enhancing the accuracy and comprehensiveness of sentiment analysis in disaster management. Exploring additional algorithms, such as deep learning models, holds promise for improving classification performance. Broadening the scope of data sources beyond Twitter to include other social media platforms and public forums would provide a more holistic view of public sentiment. Delving into the underlying reasons for negative sentiments through qualitative analysis could yield deeper insights into public concerns. Additionally, conducting longitudinal studies to track sentiment changes over time could facilitate assessing the impact of policy interventions and improvements in disaster management strategies. Moreover, developing a standard ontology for disaster-related needs and creating comprehensive disaster lexicons are crucial steps for advancing this field. Such efforts would enhance the robustness and applicability of sentiment analysis in disaster management, ultimately contributing to more effective and informed decision-making processes.

Future research, as suggested by (Sufi et al., 2023), should prioritize expanding the capabilities of the automated disaster monitoring system. This entails incorporating data from additional social media platforms, developing comprehensive disaster-related lexicons, and creating standard crisis datasets for more accurate evaluation. Further refinement of AI and NLP algorithms can improve the accuracy and precision of sentiment and location extraction. Conducting longitudinal studies to track sentiment changes over time can provide deeper insights into the impact of disaster management interventions. Additionally, exploring the integration of other data sources, such as news articles and government reports, can enhance the system's situational awareness and overall effectiveness. These advancements will contribute to a more comprehensive and responsive approach to disaster monitoring and management.

Future research should focus on expanding the capabilities of sentiment analysis in disaster management (Melvin et al., 2023). This includes incorporating data from additional social media platforms, developing comprehensive disaster-related lexicons, and creating standard crisis datasets for more accurate evaluation. Further refinement of AI and NLP algorithms can improve the accuracy and precision of sentiment analysis. Longitudinal studies tracking sentiment changes over time can provide deeper insights into the impact of disaster management interventions. Exploring the integration of other data sources, such as news articles and government reports, can enhance the system's situational awareness and overall effectiveness.

Future research should build on (Maharani, 2020) findings by expanding the scope of sentiment analysis in disaster management. This includes incorporating data from additional social media platforms, developing comprehensive disaster-related lexicons, and creating standard crisis datasets for more accurate evaluation. Further refinement of AI and NLP algorithms can improve the accuracy and precision of sentiment analysis. Longitudinal studies tracking sentiment changes over time can provide deeper insights into the impact of disaster management interventions. Exploring the integration of other data sources, such as news articles and government reports, can enhance the system's situational awareness and overall effectiveness.

Future research should build on the findings of (Choirul Rahmadan et al., 2020) by expanding the scope of sentiment analysis in disaster management. This includes incorporating data from additional social media platforms, developing comprehensive disaster-related lexicons, and creating standard crisis datasets for more accurate evaluation. Further refinement of AI and NLP algorithms can improve the accuracy and precision of sentiment analysis. Longitudinal studies tracking sentiment changes over time can provide deeper insights into the impact of disaster management interventions. Exploring the integration of other data sources, such as news articles and government reports, can enhance the system's situational awareness and overall effectiveness.

In summary, the analysis of sentiment in disaster management, particularly in the context of Jakarta's frequent flooding, reveals a predominance of negative public sentiment. This widespread dissatisfaction underscores the urgent need for improved disaster management strategies. The high performance of various machine learning and NLP models, such as SVM, Bi-LSTM, and BERT, demonstrates their effectiveness in accurately capturing public sentiment from social media data. Integrating these advanced analytical tools into disaster management frameworks can provide real-time, actionable insights, enhancing situational awareness and response strategies. Methodological reflections emphasize the importance of diverse data sources and the continuous refinement of algorithms to address the challenges of sentiment analysis.

While the reviewed studies demonstrate the potential of sentiment analysis in disaster management, significant challenges remain. The real-time processing of large volumes of social media data during a disaster event poses technical and computational challenges that need to be addressed. Future research should explore the integration of sentiment analysis with other data sources and technologies (e.g., remote sensing, IoT) to provide a more holistic view of disaster situations. Additionally, future research should focus on expanding data sources, developing comprehensive disaster-related lexicons, and conducting longitudinal studies to track sentiment changes over time. These advancements will contribute to a more responsive and informed approach to disaster management, ultimately improving public trust and the efficacy of emergency responses.

5. Conclusion

This review underscores the transformative potential of sentiment analysis in disaster management, particularly in harnessing social media data for real-time insights. The analysis of six key studies from 2018 to 2023 reveals significant progress in sentiment classification techniques, with deep learning models showing promise in handling the complexities of disaster-related social media content. The predominance of negative sentiments during disasters, as consistently reported across studies, highlights areas for improvement in disaster response and communication strategies. However, several critical challenges persist. These include the need for improved data quality and preprocessing techniques, the development of more robust multilingual analysis capabilities, and the integration of diverse data sources beyond Twitter. Additionally, ethical considerations surrounding data privacy and the potential misuse of sentiment analysis in disaster contexts require careful attention.

Future research should focus on addressing these challenges, particularly by developing standardized crisis datasets, refining models to detect specific emotions beyond general sentiment, and creating real-time monitoring systems capable of processing multi-platform data. The integration of sentiment analysis with other technologies, such as remote sensing and IoT, could provide a more comprehensive approach to disaster management. While this review offers valuable insights, it is limited by the small number of papers analyzed and its focus on recent English-language publications. Future reviews should consider a broader range of sources and languages to provide a more comprehensive global perspective.

In conclusion, as the field of sentiment analysis in disaster management continues to evolve, addressing these research gaps and challenges will be crucial for developing more effective, ethical, and responsive disaster management strategies. The potential impact on saving lives and mitigating disaster effects underscores the importance of continued research and practical application in this critical area.

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