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CRITICAL ANALYSIS OF SOCIAL MEDIA NARRATIVES ON DISASTER RESPONSE: THE 2022 CIANJUR EARTHQUAKE CASE IN INDONESIA

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ABSTRACT

This study analyzes social media narratives surrounding the 2022 Cianjur earthquake in Indonesia to understand public sentiment toward disaster response efforts. Using a comprehensive methodological approach, data was collected from Twitter, Facebook, and Instagram and processed through sentiment analysis using Logistic Regression and Naive Bayes models. The analysis categorized public responses into six sentiment classes: Support, Criticism, Rejection, Approval, Rebuttal, and Spam, while also mapping emotional distribution across Joy, Surprise, Fear, Sadness, Disgust, and Anger. Results reveal that Support was the predominant sentiment category, with approximately 4,700 instances identified by Logistic Regression and 4,000 by Naive Bayes, indicating overall public satisfaction with response efforts. Emotional analysis showed Joy (2,047 instances) and Surprise (1,691 instances) as dominant emotions, reflecting relief associated with survival and rescue operations. Both models demonstrated high accuracy, with AUC scores of 0.868 and 0.866 respectively, though they faced challenges in classifying minority sentiment categories. The findings suggest that real-time social media sentiment analysis offers valuable insights for disaster management, enabling authorities to quickly adapt communication strategies to address public concerns and misinformation. This research contributes to disaster preparedness frameworks by providing a methodological foundation for leveraging social media as a tool for gauging public sentiment during crisis events, ultimately enhancing community resilience and response effectiveness.

KEYWORDS: Sentiment Analysis, Disaster Response, Social Media, Machine Learning, Crisis Communication.

1. INTRODUCTION

For The 2022 Cianjur earthquake profoundly impacted public opinion, particularly as expressed through social media. Social media has become a primary platform for disseminating information and shaping public opinion, especially in disaster situations. During natural disasters such as earthquakes or floods, social media often serves as the first source of information accessed by the public. In these contexts, social media functions not only as a communication channel between the government and the public but also as a platform for citizens to voice opinions, complaints, and support (Alexander, 2014; Houston et al., 2015). Rapid and often unfiltered information on social media can shape public perceptions of disaster response effectiveness, influencing public trust in government and even affecting decisions related to aid and donations. (Eriksson, 2018; Veil et al., 2011). However, social media also allows for the spread of misinformation, which can worsen conditions on the ground. For example, during an earthquake, unverified reports about victim conditions or infrastructure damage can spread quickly, creating panic or false hope (Vieweg et al., 2010; Vos & Buckner, 2016). Therefore, a deep understanding of how social media narratives form and spread is crucial for effective disaster management, particularly in Indonesia, where social media penetration is high, and citizens actively use these platforms to convey both criticism and support for government disaster management efforts (Kusumasari et al., 2010).

In this regard, analyzing social media narratives is essential, as these narratives often reflect public perceptions and sentiments in real-time, providing policymakers and disaster management teams with insights to evaluate and adjust their responses. Emerging narratives on social media can reveal critical issues that may be overlooked by official authorities, such as urgent needs in specific areas or complaints regarding unequal aid distribution (Palen & Anderson, 2016; Reuter & Kaufhold, 2018). By analyzing social media communication patterns, authorities can identify areas where additional intervention may be necessary and better understand the social dynamics influencing public response to the disaster (Vieweg et al., 2010). Furthermore, social media narrative analysis can help construct more effective official narratives and respond more quickly to criticism or misinformation. For instance, during the 2022 Cianjur earthquake, analyzing social media discussions may reveal public dissatisfaction with the speed of government response, which can then be used to improve on-ground coordination and communication (Zhai et al., 2023). In the long term, better understanding of social media narratives can enhance future disaster preparedness and mitigation, ensuring that disaster responses are more responsive to public needs and expectations (Stieglitz et al., 2018; Zook et al., 2010).

The 2022 Cianjur earthquake is one of Indonesia's significant natural disasters, highlighting the challenges of disaster management in the digital era. Occurring in November 2022, the Cianjur earthquake was one of the most destructive events in Indonesia in recent years, with a magnitude of 5.6 and an epicenter at a depth of 10 kilometers near densely populated areas of Cianjur, West Java. Despite its moderate magnitude, the earthquake caused extensive damage due to its shallow depth and proximity to populated areas. Consequently, over 300 fatalities were reported, with thousands injured and tens of thousands of homes severely damaged or destroyed (Prayogo, 2023). This disaster also caused widespread infrastructure damage in Cianjur and surrounding areas, triggered landslides in some regions, and worsened the situation, complicating access to affected areas and increasing the death toll (Hutabarat et al., 2024). In addition to physical damage, the earthquake sparked a substantial wave of social media discussions, with the public voicing various criticisms and support for the response by the government and related agencies. Analyzing social media conversations during and after the disaster reveals important aspects of disaster management, from the speed of aid distribution to inter-agency coordination (Kim & Hastak, 2018). Amid this, the early response from both the government and the public played a crucial role in rescue and recovery efforts. The government's initial response involved deploying emergency response teams from the National Disaster Management Agency (BNPB), the military, the police, and various other agencies, focusing on victim evacuation, setting up refugee shelters, and distributing logistical aid, such as food, clean water, and medicine. Meanwhile, local communities and volunteers from various regions quickly mobilized to assist in the rescue process, provide aid, and set up public kitchens for refugees (Kusumasari et al., 2010). At the same time, social media became a critical tool for the public to spread information, coordinate aid, and voice complaints regarding delayed aid distribution and lack of inter-agency coordination (Mavrodieva & Shaw, 2021).

As a case study, the 2022 Cianjur earthquake offers valuable insights into how social media can serve as a tool for understanding public perception

and improving disaster response. Although social media can be a rapid and extensive source of information, challenges in verifying information and managing public narratives remain issues that need to be addressed (Kusumasari et al., 2010). In this context, it is crucial for government and non-governmental organizations not only to focus on on-the-ground disaster management but also to proactively manage social media narratives to ensure that accurate information is disseminated to the public.

Literature on disaster response in Indonesia has shown that earthquakes, as one of the country's most frequent natural disasters, often expose weaknesses in emergency response systems, particularly in terms of inter-agency coordination and aid distribution (Prasojo et al., 2021). Studies on disaster management literacy in Indonesia also reveal that while efforts have been made to improve early warning systems and community preparedness, implementation is often uneven, especially in areas distant from central government or with weak infrastructure (Mujiburrahman, 2018). Literature further underscores the crucial role of social media in disaster response, which has become an essential tool in crisis communication. Numerous studies have identified that social media functions as a platform for rapid information exchange, field condition reporting, and real-time aid mobilization (Logayah et al., 2023). On the other hand, social media can also amplify rumors and unverified information, which can hinder emergency response effort (Torpan et al., 2021). In the context of the Cianjur earthquake, literature records widespread social media usage by residents to report their conditions, demand assistance, and organize social solidarity.

Further, previous studies on disaster response in Indonesia highlight a systematic tendency to prioritize technical aspects of disaster management, such as logistics and infrastructure, over the social and psychological aspects that are also crucial for the recovery of affected communities (Partelow, 2020). In the case of the Cianjur earthquake, for instance, the government's initial response was criticized for its lack of attention to the psychosocial needs of the victims, which is essential for the recovery process (Dwi et al., 2023). This recent, large-scale disaster underscores challenges in coordination, aid distribution, and addressing the psychosocial needs of victims. In the digital age, social media has become the primary platform for the public to voice their experiences and opinions on disaster response. Despite the significant role social media plays in shaping public opinion, a deeper understanding of how social media narratives reflect public sentiment toward disaster response remains limited. Key questions emerge, such as: how does social media reflect public sentiment toward government and community response in the 2022 Cianjur earthquake? What dominant narratives appear on social media related to the Cianjur disaster response? How do these narratives influence public perceptions of the emergency response efforts? What role does social media play in shaping public opinion and influencing policy in the context of disaster response? This study aims to provide deeper insights into the relationship between social media, public sentiment, and disaster response, offering recommendations that can be used by the government and related agencies to enhance disaster response effectiveness in the future.

This research is important for four reasons. First, analyzing social media narratives provides direct insights into the feelings, needs, and expectations of communities affected by disasters. By understanding public sentiment, the government and humanitarian organizations can respond more quickly and accurately to on-ground needs. In the context of the Cianjur earthquake, where there was criticism of the government's slow response, this research can help identify weaknesses in disaster management and encourage policy improvements and more efficient emergency response implementation in the future. Second, social media often becomes a place for the public to express dissatisfaction with government disaster response efforts. Criticism on social media during the Cianjur earthquake highlights communication gaps between the government and affected residents. Narrative analysis can reveal areas where government information is poorly communicated or where crisis communication needs to be enhanced. This is vital for building public trust and ensuring that future disaster response efforts can be managed more effectively. Third, social media has great potential as a tool for coordinating aid and mobilizing resources during disasters. However, its effectiveness depends on how social media narratives are analyzed and utilized. In the case of the Cianjur earthquake, where there was significant criticism regarding delayed aid, this research can help identify ways social media can be used more effectively to expedite response and aid mobilization and improve coordination among various stakeholders. Fourth, this discussion is not only important for current emergency response but also for future disaster mitigation strategies. By studying how the public reacted and interacted on social media during the Cianjur earthquake, the

government and related organizations can formulate better strategies for future disaster preparedness. This includes enhancing public education on disaster mitigation, improving emergency response protocols, and ensuring infrastructure and logistical preparedness on a larger scale.

2. LITERATURE REVIEW

2.1. Social Media and Disaster Response

Social media has become an increasingly vital tool in disaster response, facilitating rapid and widespread communication among governments, relief organizations, and affected communities. Research indicates that platforms such as Twitter, Facebook, and Instagram play crucial roles in disseminating emergency information, coordinating aid, and amplifying the voices of disaster victims (Houston et al., 2015; Liu et al., 2013). Social media not only serves as a channel for vertical communication from authorities to the public but also enables horizontal communication among individuals, enhancing community coordination and solidarity (Palen & Anderson, 2016; Vieweg et al., 2010).

Previous studies have identified various ways in which social media influences disaster response. For instance, Lachlan et al. (2014) found that social media helps reduce uncertainty during crises by providing real-time updates. Meanwhile, Stieglitz et al. (2018) highlighted that social media also serves as a platform for expressing emotions and grievances, which can offer valuable insights for authorities to understand the urgent needs of the public.

2.2. Public Sentiment Analysis

Analyzing public sentiment through social media is an evolving field of research, particularly in the context of natural disasters. Public sentiment, which encompasses the feelings, opinions, and reactions of people to specific events, can be measured through text posted on social media. Common sentiment analysis techniques include lexicon-based approaches, machine learning-based analysis, and topic analysis (Cambria et al., 2013).

The lexicon-based approach typically involves matching words in a text with a list of words classified as positive, negative, or neutral (Taboada et al., 2011). Alternatively, machine learning-based The unstructured nature of social media data required extensive preprocessing to ensure clarity for sentiment analysis. Preprocessing was performed using Orange 3, a visual programming tool for data mining and machine learning. Initial steps involved removing extraneous elements, including hyperlinks, emojis, and user mentions, which, though common in social media, add noise to text data (Keller, 2014; Vieweg et al., 2010). Standardizing text through normalization, including converting characters to lowercase and correcting spelling errors, facilitated consistency across entries. Finally, irrelevant stop words were removed to enhance sentiment analysis accuracy, allowing for a more precise focus on sentiment-driven terms (Stieglitz et al., 2018; Zook et al., 2010).approaches employ algorithms such as Naive Bayes, Logistic Regression, and Support Vector Machines to predict sentiment based on features extracted from the text (Pang & Lee, 2008). Topic analysis, such as Latent Dirichlet Allocation (LDA), is used to identify dominant themes or topics emerging from public discussions on social media (Blei et al., 2001).

2.3. Case Studies on Social-Media in Previous Disasters

Several case studies have examined the role of social media in previous disasters, providing essential context for this research. For example, a study on the 2004 Aceh tsunami found that social media, although still in its early stages, was used to coordinate aid and disseminate information among the Indonesian diaspora and the international community (Alvisyahrin et al., 2023). Research on the 2018 Lombok earthquake revealed that social media became a primary information source for local communities and refugees and was used to organize humanitarian aid (Carley et al., 2016).

Lessons from these cases demonstrate that social media serves not only as a communication tool but also as a barometer of public sentiment. Public responses recorded on social media often influence policy decisions and assist authorities and non-governmental organizations in adjusting their strategies to meet the needs and expectations of the community (Alexander, 2014; Reuter & Kaufhold, 2018). This study aims to continue this tradition, focusing on the 2022 Cianjur earthquake, to explore how social media reflects and shapes public sentiment toward disaster response efforts.

3. METHODS

Data was gathered from prominent social media platforms, specifically Twitter, Facebook, and Instagram, due to their extensive use in Indonesia and capacity to capture real-time public responses to critical events like the 2022 Cianjur earthquake. This choice aligns with the study's objective to evaluate social narratives and public sentiment toward disaster responses (Alexander, 2014; Houston et al.,

2015). The data collection process employed a keyword-based scraping technique, using specific hashtags and terms related to the earthquake to isolate relevant posts. To facilitate structured data collection, APIs such as the Twitter API and tools like exportcomment.com were utilized, allowing access to a comprehensive dataset reflecting diverse public opinions and discussions around the disaster (Palen & Anderson, 2016; Reuter & Kaufhold, 2018).

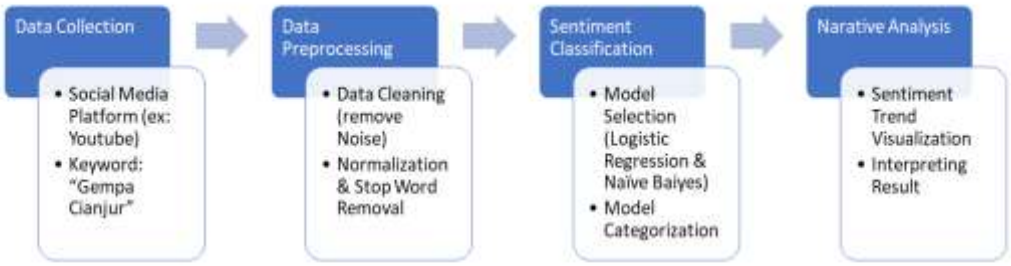

Figure 1: Methodological Workflow.

For sentiment classification, logistic regression and Naive Bayes models were selected due to their efficacy in text-based tasks (Pang & Lee, 2008). These models were trained on a labeled dataset to categorize sentiments into six distinct classes: support, criticism, rejection, approval, rebuttal, and spam. Logistic regression was employed for its effectiveness in discerning sentiment polarity, while Naive Bayes, based on Bayes' theorem, excelled at handling categorical outputs in text (Cambria et al., 2013; Taboada et al., 2011). This combination provided a nuanced classification of sentiments, enabling a detailed interpretation of public reactions to disaster response efforts (Eriksson, 2018; Veil et al., 2011).

To interpret sentiment trends and dynamics over time, Orange 3 was used to create initial visualizations of sentiment patterns. More complex network analyses were conducted using Gephi, which mapped user connections, comments, and sentiment clusters to reveal underlying social dynamics within the disaster response context (Carley et al., 2016; Lachlan et al., 2014). Python libraries Matplotlib and Seaborn further enabled customized, advanced visualizations, providing deeper insights into how public sentiment evolved in response to the earthquake and revealing critical periods for targeted response (Starbird et al., 2014; Vos & Buckner, 2016).

4. RESULTS

4.1. Data Preprocessing Pipeline and Sentiment Analysis Workflow

The analysis began with a comprehensive data preprocessing pipeline, essential for transforming raw social media content into a structured format suitable for sentiment classification. Utilizing Orange 3, a versatile visual programming tool, data preprocessing followed a meticulous sequence. Initially, extraneous elements such as hyperlinks, emojis, and user mentions were removed. These non-textual elements are commonplace in social media posts and can introduce significant noise, making it difficult for machine learning models to capture sentiment accurately. This step ensured that only relevant text remained, forming a clean foundation for further processing. Standardization followed, with all text converted to lowercase and spelling errors corrected to maintain uniformity across entries. Finally, non-essential stop words were eliminated, allowing the models to focus solely on sentiment-driving words and terms. The refined dataset, now free from irrelevant or redundant information, became ready for the subsequent sentiment analysis.

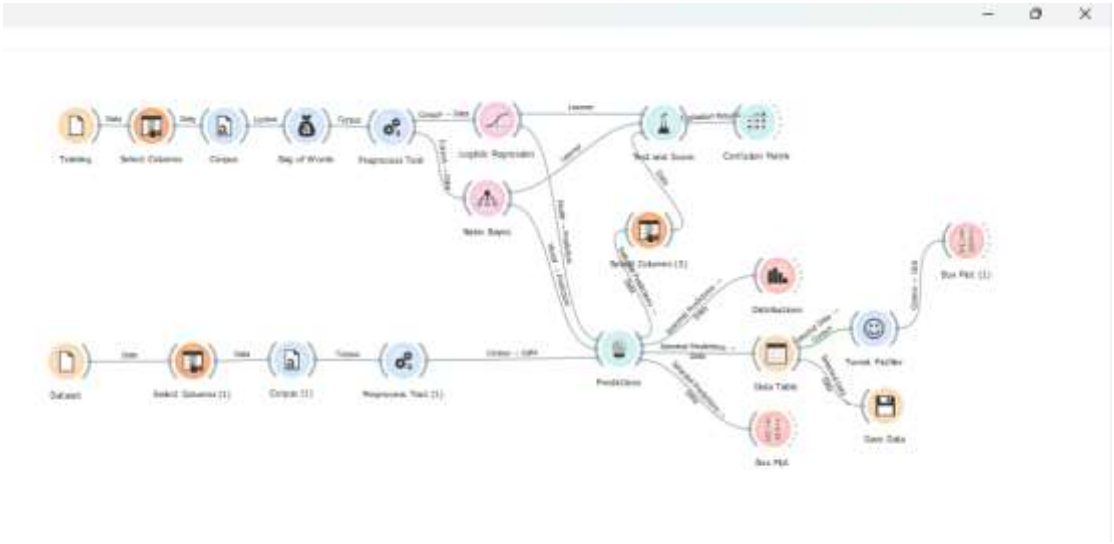

Figure 2: Orange 3 Workflow Processing.

Following preprocessing, the sentiment classification workflow commenced with the training of two machine learning models—Logistic Regression and Naive Bayes—chosen for their proven effectiveness in text classification. These models, each offering distinct advantages in handling textual sentiment, were tailored to classify social media responses into six specific categories: Support, Criticism, Rejection, Approval, Rebuttal, and Spam. Logistic Regression was selected for its strength in identifying sentiment polarity, leveraging a linear approach to distinguish between positive and negative tones in posts. Naive Bayes, on the other hand, was incorporated due to its probabilistic framework, which handles categorical outputs proficiently and is particularly efficient with labeled textual data. Together, these models enabled a multi-faceted view of public sentiment, allowing for a nuanced interpretation of reactions to the disaster response efforts.

4.2. Data Pre-processing Pipeline and Sentiment Analysis Workflow

4.2.1. Emotional Distribution Analysis

Figure 3 presents a detailed analysis of the primary emotions expressed across social media posts related to the 2022 Cianjur earthquake, categorized into six key emotions: Joy, Surprise, Fear, Sadness, Disgust, and Anger. These emotions provide a granular view of the collective public sentiment during and after the earthquake. Joy emerged as the most frequently occurring emotion, with over 2,000 instances observed. This may initially seem unexpected, given the severity of the disaster, yet it likely reflects sentiments of resilience and relief associated with rescue efforts and the survival of loved ones. The public's ability to find hope amid adversity aligns with prior studies on disaster sentiment, where relief and survival often foster a sense of communal joy and solidarity.

Surprise, the second most common emotion, appeared in 1,691 instances, likely capturing the initial shock experienced by many in response to the earthquake's unexpected scale and impact. As social media serves as a rapid information source, the sheer volume of posts in the Surprise category highlights how the public used these platforms to share their astonishment and exchange information. Fear also registered prominently, with over 1,100 mentions, indicating a prevalent concern regarding the earthquake's aftermath and potential aftershocks. This collective anxiety underscores the vulnerability felt by affected communities, further emphasizing the emotional toll that disasters can inflict beyond the physical damage. Sadness, with 327 mentions, reflects empathy and sorrow for the lives lost and the extensive property damage sustained by communities.

Conversely, the relatively low instances of Disgust (167 mentions) and Anger (146 mentions) suggest that, while some negative reactions were present, these were not the dominant emotions. These sentiments likely arose from frustrations over perceived inefficiencies or delays in disaster management. The statistical significance of this emotional distribution ($\chi^2 = 27865.00$, $p < 0.001$) confirms considerable variation in emotional responses, with Joy and Surprise as the most dominant, underscored by notable instances of Fear and Sadness, each emotion painting a vivid picture of the public's reaction to the disaster and its

response.

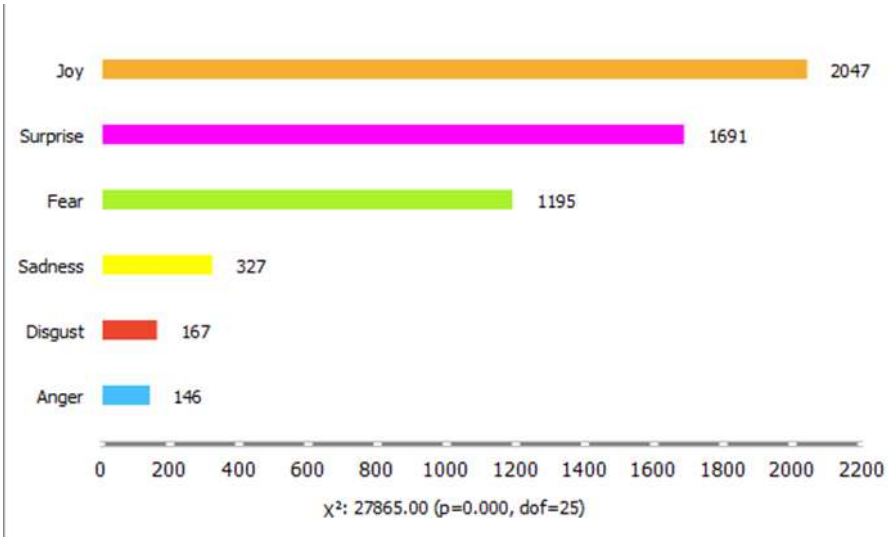

Figure 3: Emotional Distribution by Eckman Class.

4.3. Data Pre-processing Pipeline and Sentiment Analysis Workflow

4.3.1. Sentiment Category Distribution

Figures 4 and 5 display the results of the sentiment classification, highlighting the distribution across six sentiment categories as processed by the Logistic Regression and Naive Bayes models, respectively. This distribution is essential in understanding the public's reactions, both supportive and critical, of the disaster response. The Support category overwhelmingly dominated in both models, with approximately 4,700 instances in Logistic Regression and close to 4,000 in Naive Bayes. These figures signify a predominantly positive public response, indicative of general satisfaction with response efforts and resilience-building measures undertaken by local agencies and communities.

Approval, a secondary form of positive sentiment, appeared with lesser frequency, showing a moderate level of public acknowledgment of the government and community-led responses. Logistic Regression identified 269 instances of Approval, while Naive Bayes recorded only 84, indicating a discrepancy likely influenced by each model's inherent approach to text classification. The presence of Spam, recorded at 264 and 142 instances across both models, respectively, further emphasizes the challenges associated with social media analysis, where irrelevant content can interfere with sentiment classification. The classification models identified Spam effectively, removing non-sentiment data to preserve the analysis's integrity.

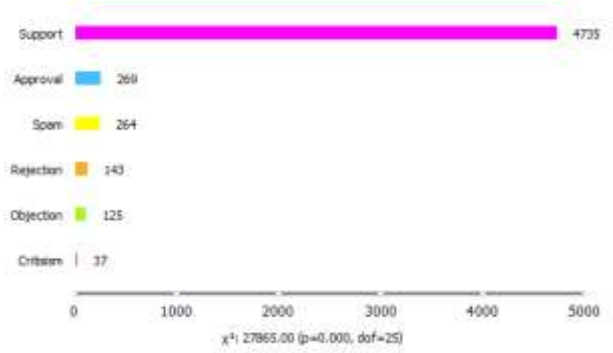

Figure 4: Sentiment Categories–Logistic Regression.

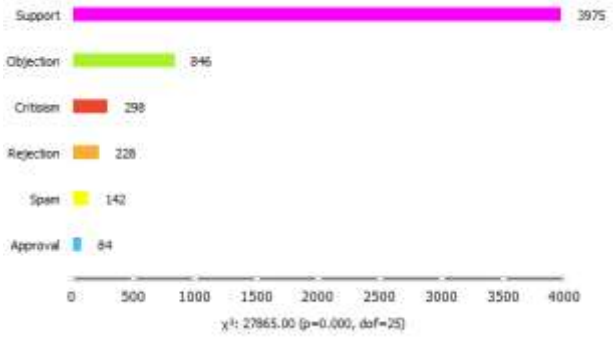

Figure 5: Sentiment Categories-Naïve Baiyes.

Among negative sentiments, Rejection appeared with 143 and 228 mentions across the models, representing pockets of dissatisfaction, potentially tied to localized issues or perceived inefficiencies. Objection, with counts of 125 and 846, captured public dissent and alternative viewpoints regarding official narratives. Criticism, the least frequent

sentiment, had 37 mentions in Logistic Regression and 298 in Naive Bayes, a variation that highlights the differences in each model's sensitivity to detecting nuanced dissent. Chi-square analysis (χ^2 = 27865.00, $p < 0.001$) confirms substantial variation among these categories, with Support being the predominant sentiment, while Rejection and Criticism expose areas of public concern requiring attention and improvement.

4.4. Data Pre-processing Pipeline and Sentiment Analysis Workflow

4.4.1. Model Performance

The Logistic Regression and Naive Bayes models were evaluated based on standard metrics, including Area Under the Curve (AUC), Classification Accuracy (CA), F1 Score, Precision, Recall, and Matthews Correlation Coefficient (MCC). The Logistic Regression model achieved an AUC of 0.868, CA of 0.860, F1 score of 0.813, precision of 0.790, recall of 0.860, and MCC of 0.275, reflecting high accuracy and recall, which aligns with similar studies showing Logistic Regression's effectiveness in handling large datasets (Chen et al., 2019; Golpour et al., 2020). Comparatively, Naive Bayes demonstrated comparable results, with an AUC of 0.866, CA of 0.860, F1 score of 0.818, precision of 0.795, recall of 0.860, and MCC of 0.291. The Naive Bayes model slightly outperformed Logistic Regression in F1 score and MCC, indicating a better balance between precision and recall, particularly for minority categories. These performance results confirm both models' strengths, with Naive Bayes providing a marginally superior performance in categorizing less frequent responses (Aziz et al., 2023; Bahtiar et al., 2023).

Model	AUC	CA	F1	Prec	Recall	MCC
Logistic Regression	0.868	0.860	0.813	0.790	0.860	0.275
Naive Bayes	0.866	0.860	0.818	0.795	0.860	0.291

Figure 6: Model Performance Comparison.

4.5. Data Pre-processing Pipeline and Sentiment Analysis Workflow

4.5.1. Confusion Matrix Analysis

The confusion matrices presented in Figures 7 and 8 offer insights into the classification accuracy of both models across sentiment categories. Logistic Regression performed well in identifying the Support category, accurately classifying 4,676 instances with minimal misclassifications into other categories, highlighting the model's strength in capturing this dominant sentiment. However, for minority classes like Approval and Objection, minor misclassifications were observed. These errors indicate that while Logistic Regression is adept at handling predominant categories, it encounters limitations in accurately classifying less frequent sentiments, likely due to limited features or subtle differences between certain sentiments.

Naive Bayes, similarly, displayed strong accuracy for Support, correctly classifying 4,660 instances. Nonetheless, challenges arose in distinguishing minority sentiments, with some misclassification observed, notably with Support instances occasionally misclassified as Objection. This trend reveals that while both models effectively capture the overall sentiment trends, their performance is less reliable when distinguishing between minority categories like Criticism and Approval. Naive Bayes, however, exhibited a slightly better balance in handling these smaller classes, as reflected in its marginally higher Matthews Correlation Coefficient (MCC), suggesting a probabilistic advantage in managing categorical sentiment data. These findings underscore the need for further refinement to enhance classification accuracy, particularly for nuanced sentiments that reflect critical perspectives on disaster response.

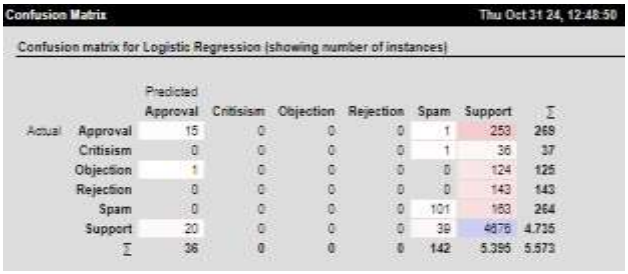

Figure 7: Confusion Matrix Logistic Regression.

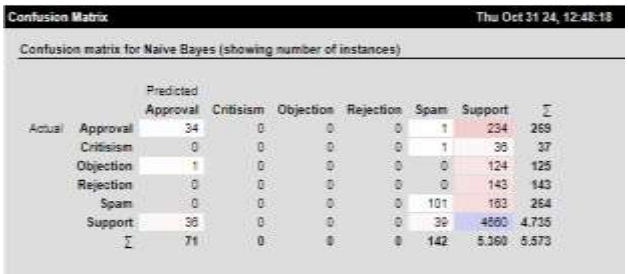

Figure 8: Confusion Matrix Naïve Bayes.

The results of this analysis provide a vital understanding of public sentiment during the 2022 Cianjur earthquake, underscoring the centrality of Support and Joy as dominant themes that reflect general public endorsement of response measures. However, the presence of negative sentiments like

Rejection and Criticism highlights areas where disaster management strategies can be improved. By enabling disaster response agencies to monitor real-time sentiment trends on social media, this analytical approach offers a proactive way to assess public reactions and adjust communication strategies to address concerns promptly. The observed challenges in classifying minority categories suggest the need for advanced machine learning techniques, potentially incorporating ensemble methods or transformer-based models like BERT, to enhance the models' sensitivity to less frequent but critical public sentiments. This improvement would enable authorities to capture a broader range of perspectives, providing a more nuanced and comprehensive understanding of community needs in times of crisis.

Ultimately, integrating sentiment analysis into disaster management frameworks facilitates a more informed, responsive approach to public communication. By observing the evolution of sentiments, agencies can engage with communities in meaningful ways, promoting transparency, addressing misinformation, and fostering public cooperation. This approach not only strengthens disaster preparedness but also enhances resilience, with social media playing a pivotal role in modern disaster response.

5. DISCUSSION

Understanding the sentiment patterns observed in this study requires situating the findings within Indonesia's distinctive socio-cultural framework, where traditional collective values fundamentally shape digital disaster communication behaviors. The predominance of Support sentiment (4,735 instances in Logistic Regression analysis) reflects Indonesia's deeply embedded cultural principle of gotong royong (mutual assistance), which emphasizes community solidarity and collective responsibility during crisis situations (Slikkerveer, 2019) . This cultural orientation toward communal resilience provides critical context for interpreting why supportive expressions vastly outnumbered critical sentiments, suggesting that cultural norms prioritize collective harmony over individual grievances during disasters.

Unlike traditional, retrospective assessments, this approach enables policymakers to quickly interpret public sentiment as events unfold, providing an innovative methodology for understanding public opinion on social media and guiding government and NGO disaster response strategies (Rudyawan et al., 2023). By utilizing real-time social media data, this research emphasizes a dynamic approach to evaluating disaster response effectiveness, which is essential in a digital age where social media serves as a primary platform for public communication during crises (Contreras et al., 2022).

The emotional distribution in social media posts revealed that Joy and Surprise were dominant emotions, with Joy appearing 2,047 times and Surprise 1,691 times. While this may seem unexpected given the severity of the disaster, these emotions likely reflect public relief related to the survival of loved ones and successful rescue efforts. The prevalence of Surprise suggests astonishment at the unexpected intensity of the earthquake and the rapid information spread on social media. This is consistent with findings from studies on disaster sentiment, where social media provides a platform for expressing resilience and solidarity during crises (Crooks et al., 2013; Houston et al., 2015). Support was the most frequent response category, appearing 4,735 and 3,975 times across datasets, signaling strong public endorsement of the disaster response efforts. The relatively low counts of Criticism and Rejection suggest a generally positive perception of the response efforts (Wong-Villacres et al., 2017). However, instances of Spam (264 and 142) and Objection (125 and 846) indicate that some irrelevant or dissenting content circulated within the datasets, emphasizing the need for effective data filtering to maintain analysis accuracy (Prayogo, 2023).

Both the Logistic Regression and Naive Bayes models achieved high accuracy in classifying sentiments, as reflected by their AUC, F1 scores, and precision metrics. However, there were subtle differences in their performance across various sentiment categories, which offer insights into each model's strengths and limitations.

- Logistic Regression demonstrated strong precision and recall in predicting dominant categories like Support and Approval, successfully minimizing false positives in these classes. However, it struggled with minority classes, as seen in its misclassification of Criticism and Objection as Support. This misclassification tendency indicates that Logistic Regression may not be sensitive enough to detect nuanced distinctions in minority categories, which require more refined feature representation.
- Naive Bayes, on the other hand, performed similarly well with major categories and showed a slightly better balance in handling smaller classes, reflected in a higher MCC. Its probabilistic nature allows it to estimate class

probabilities more effectively, which can be advantageous in distinguishing less frequent sentiments like Criticism and Rejection. Despite this, Naive Bayes also exhibited challenges with minority classes, although it demonstrated a marginally better capability in capturing Approval and Objection compared to Logistic Regression.

This comparative analysis highlights that while both models are reliable for predominant categories, their limitations with minority sentiment categories suggest room for improvement. Future iterations could incorporate ensemble methods or more advanced NLP techniques, such as transformer-based models (e.g., BERT), which are better equipped to capture contextual nuances and subtle sentiment variations. Such improvements would enhance the models' ability to interpret a broader range of public sentiments, particularly in complex social media narratives around disaster events.

The results demonstrate the potential of real-time social media sentiment analysis in disaster management. By analyzing public sentiment on social media, disaster response agencies can quickly adapt their communication strategies to meet public expectations. The dominance of Support and Joy suggests positive public reception of the response efforts, which can reinforce public morale and cooperation. Monitoring Fear or Criticism spikes could also allow agencies to proactively address misinformation and alleviate public concerns (Eriksson, 2018). This approach aligns with existing literature on social media's role in disaster communication, underscoring its potential in managing public perception and misinformation (Veil et al., 2011).

This study's reliance on platforms such as Twitter, Facebook, and Instagram may not fully represent broader public sentiment, particularly among demographics with limited social media access. Additionally, the models faced limitations in accurately classifying ambiguous sentiments, suggesting the need for advanced NLP methods in future studies. Incorporating a wider range of sentiment categories or analyzing longitudinal social media data throughout the recovery period could provide a more nuanced understanding of public sentiment over time. Expanding analysis to additional platforms like WhatsApp or TikTok could also capture a more comprehensive view of public opinion (Rivera-Loaiza et al., 2018) .

This study underscores the importance of social media sentiment analysis in disaster response, demonstrating how real-time public sentiment data can inform and enhance disaster management efforts. By systematically categorizing public sentiment through machine learning, this research provides a valuable tool for government and NGO response teams, emphasizing a proactive approach to disaster communication. Ultimately, this work contributes to the framework for using social media in disaster preparedness and response, aiming to strengthen community resilience in future crises.

6. CONCLUSION

This study demonstrates the value of social media sentiment analysis in disaster response, using the 2022 Cianjur earthquake as a case study. By applying machine learning models, Logistic Regression and Naive Bayes, to analyze public sentiment on platforms like Twitter, Facebook, and Instagram, this research captures a real-time snapshot of community emotions and responses. The prominence of Joy and Surprise suggests a resilient public spirit and appreciation for response efforts, while the dominance of Support in response categories indicates positive public alignment with government and community actions.

The high accuracy of the sentiment classification models validates their application for large-scale, real-time sentiment analysis in crisis contexts. However, challenges in distinguishing nuanced categories such as Criticism and Objection highlight areas for methodological improvement. Future research could refine these models with advanced NLP techniques and include additional platforms to capture a broader demographic, thereby providing more comprehensive insights.

Ultimately, this study supports the integration of social media monitoring into disaster management frameworks, as it enables authorities to gauge community sentiment and respond proactively. Real-time sentiment insights allow for tailored communication strategies, fostering trust and engagement in times of crisis. This approach contributes to a more resilient and informed society, with social media playing a critical role in modern disaster preparedness and response.

REFERENCES

Alexander, D. E. (2014). Social Media in Disaster Risk Reduction and Crisis Management. Science and Engineering Ethics, 20(3), 717–733. https://doi.org/10.1007/s11948-013-9502-z

Alvisyahrin, T., Husin, T., Oktabina, R. W., & Sunarty, R. (2023). Aceh Post 2004 Tsunami Recovery: Strategies and Implications. In Y. Kaneko, T. Alvisyahrin, T. B. Muhammad Husin, J. Wang, & E. R. Florano (Eds.), Recovery of Disaster Victims (pp. 171–179). Springer Nature Singapore. https://doi.org/10.1007/978-981-99-2957-3_4

Aziz, M. M., Purbalaksono, M. D., & Adiwijaya, A. (2023). Method comparison of Naïve Bayes, Logistic Regression, and SVM for Analyzing Movie Reviews. Building of Informatics, Technology and Science (BITS), 4(4). https://doi.org/10.47065/bits.v4i4.2644

Bahtiar, S. A. H., Dewa, C. K., & Luthfi, A. (2023). Comparison of Naïve Bayes and Logistic Regression in Sentiment Analysis on Marketplace Reviews Using Rating-Based Labeling. Journal of Information Systems and Informatics, 5(3), 915–927. https://doi.org/10.51519/journalisi.v5i3.539

Blei, D., Ng, A., & Jordan, M. (2001). Latent Dirichlet Allocation. In The Journal of Machine Learning Research (Vol. 3, p. 608).

Cambria, E., Schuller, B., Xia, Y., & Havasi, C. (2013). New Avenues in Opinion Mining and Sentiment Analysis. IEEE Intelligent Systems, 28(2), 15–21. https://doi.org/10.1109/MIS.2013.30

Carley, K. M., Malik, M., Landwehr, P. M., Pfeffer, J., & Kowalchuck, M. (2016). Crowd sourcing disaster management: The complex nature of Twitter usage in Padang Indonesia. Safety Science, 90, 48–61. https://doi.org/10.1016/j.ssci.2016.04.002

Chen, W., Yan, X., Zhao, Z., Hong, H., Bui, D. T., & Pradhan, B. (2019). Spatial prediction of landslide susceptibility using data mining-based kernel logistic regression, naive Bayes and RBFNetwork models for the Long County area (China). Bulletin of Engineering Geology and the Environment, 78(1), 247–266. https://doi.org/10.1007/s10064-018-1256-z

Contreras, D., Wilkinson, S., Aktas, Y. D., Fallou, L., Bossu, R., & Landès, M. (2022). Intensity-Based Sentiment and Topic Analysis. The Case of the 2020 Aegean Earthquake. Frontiers in Built Environment, 8, 839770. https://doi.org/10.3389/fbuil.2022.839770

Crooks, A., Croitoru, A., Stefanidis, A., & Radzikowski, J. (2013). #Earthquake: Twitter as a Distributed Sensor System. Transactions in GIS, 17(1), 124–147. https://doi.org/10.1111/j.1467-9671.2012.01359.x

Dwi, W., Sutisna2, L. S., Widodo4, P., Juni, H., & Saragih5, R. (2023). The Strategy of Housing Rehabilitation and Reconstruction after 2022 Earthquake in Cianjur, West Java, Indonesia. International Journal Of Humanities Education and Social Sciences (IJHESS). https://doi.org/10.55227/ijhess.v2i5.454

Eriksson, M. (2018). Lessons for Crisis Communication on Social Media: A Systematic Review of What Research Tells the Practice. International Journal of Strategic Communication, 12(5), 526–551. https://doi.org/10.1080/1553118X.2018.1510405

Golpour, P., Ghayour-Mobarhan, M., Saki, A., Esmaily, H., Taghipour, A., Tajfard, M., Ghazizadeh, H., Moohebati, M., & Ferns, G. A. (2020). Comparison of Support Vector Machine, Naïve Bayes and Logistic Regression for Assessing the Necessity for Coronary Angiography. International Journal of Environmental Research and Public Health, 17(18), 6449. https://doi.org/10.3390/ijerph17186449

Houston, J. B., Hawthorne, J., Perreault, M. F., Park, E. H., Goldstein Hode, M., Halliwell, M. R., Turner McGowen, S. E., Davis, R., Vaid, S., McElderry, J. A., & Griffith, S. A. (2015). Social media and disasters: A functional framework for social media use in disaster planning, response, and research. Disasters, 39(1), 1–22. https://doi.org/10.1111/disa.12092

Hutabarat, L. E., Simanjuntak, P., Tambunan, E., & Purnomo, C. C. (2024). Geotechnical Review of Building Damage and Landslide After Cianjur Earthquake 2022. Riau Journal of Empowerment, 7(2), 111–124. https://doi.org/10.31258/raje.7.2.111-124

Keller, B. (2014). Social media in disaster response: How experience architects can build for participation by L. Potts, (2013). New York, NY: Routledge. Communication Design Quarterly, 2(2), 39–42. https://doi.org/10.1145/2597469.2597476

Kim, J.-H., & Hastak, M. (2018). Social network analysis: Characteristics of online social networks after a disaster. Int. J. Inf. Manag., 38, 86–96. https://doi.org/10.1016/j.ijinfomgt.2017.08.003

Kusumasari, B., Alam, Q., & Siddiqui, K. (2010). Resource capability for local government in managing disaster. Disaster Prevention and Management: An International Journal, 19(4), 438–451. https://doi.org/10.1108/09653561011070367

Lachlan, K. A., Spence, P. R., Lin, X., & Del Greco, M. (2014). Screaming into the Wind: Examining the Volume and Content of Tweets Associated with Hurricane Sandy. Communication Studies, 65(5), 500–518. https://doi.org/10.1080/10510974.2014.956941

Liu, J., Song, M., Horton, R. M., & Hu, Y. (2013). Reducing spread in climate model projections of a September ice-free Arctic. Proceedings of the National Academy of Sciences, 110(31), 12571–12576. https://doi.org/10.1073/pnas.1219716110

Logayah, D. S., Maryani, E., Ruhimat, M., & Wiyanarti, E. (2023). Understanding Disaster Literacy Level in Indonesia: How can students understand natural disasters? AL-ISHLAH: Jurnal Pendidikan, 15(4), 4962–4971. https://doi.org/10.35445/alishlah.v15i4.3648

Mavrodieva, A. V., & Shaw, R. (2021). Social Media in Disaster Management. Media and Disaster Risk Reduction, 55–73. https://doi.org/10.1007/978-981-16-0285-6_4

Mujiburrahman, M. (2018). The role of universities in Indonesia multi-hazard early warning system. 229, 1–8. https://doi.org/10.1051/matecconf/201822902018

Palen, L., & Anderson, K. M. (2016). Crisis informatics—New data for extraordinary times. Science, 353(6296), 224–225. https://doi.org/10.1126/science.aag2579

Pang, B., & Lee, L. (2008). Opinion Mining and Sentiment Analysis. Foundations and Trends® in Information Retrieval, 2(1–2), 1–135. https://doi.org/10.1561/1500000011

Partelow, S. (2020). Social capital and community disaster resilience: Post-earthquake tourism recovery on Gili Trawangan, Indonesia. Sustainability Science, 16, 203–220. https://doi.org/10.1007/s11625-020-00854-2

Prasojo, A. P. S., Surtiari, G. A. K., & Prasetyoputra, P. (2021). The impact of natural disasters in Indonesia: How does welfare accentuate and attenuate the loss of people? Journal of Physics: Conference Series, 1869(1), 012148. https://doi.org/10.1088/1742-6596/1869/1/012148

Prayogo, M. A. (2023). Analysis of Land Cover and Building Damage Due to The 21th November 2022 Cianjur Earthquake using Sentinel-2. IOP Conference Series: Earth and Environmental Science, 1276(1), 012037. https://doi.org/10.1088/1755-1315/1276/1/012037

Reuter, C., & Kaufhold, M. (2018). Fifteen years of social media in emergencies: A retrospective review and future directions for crisis Informatics. Journal of Contingencies and Crisis Management, 26(1), 41–57. https://doi.org/10.1111/1468-5973.12196

Rivera-Loaiza, C., Domínguez-Mota, F. J., López-Huerta, M. I., & Santana-Quintero, D. (2018). A Tale of Two Earthquakes: Analyzing Social Media Responses in Natural Disasters. In C. Stephanidis (Ed.), HCI International 2018 – Posters' Extended Abstracts (Vol. 850, pp. 439–443). Springer International Publishing. https://doi.org/10.1007/978-3-319-92270-6_63

Rudyawan, A., Pamumpuni, A., Puspaningrum, M. R., Gunawan, I., Sapiie, B., Handayani, A. P., & Abdurrachman, M. (2023). Cianjur Earthquake- Roles of Social Media and the Distribution of Sciences. IOP Conference Series: Earth and Environmental Science, 1245(1), 012016. https://doi.org/10.1088/1755-1315/1245/1/012016

Slikkerveer, L. (2019). Gotong Royong: An Indigenous Institution of Communality and Mutual Assistance in Indonesia (pp. 307–320). https://doi.org/10.1007/978-3-030-05423-6_14

Starbird, K., Maddock, J., Orand, M., Achterman, P., & Mason, R. M. (2014, March 1). Rumors, False Flags, and Digital Vigilantes: Misinformation on Twitter after the 2013 Boston Marathon Bombing. iConference 2014 Proceedings. iConference 2014 Proceedings: Breaking Down Walls. Culture - Context - Computing. https://doi.org/10.9776/14308

Stieglitz, S., Mirbabaie, M., Ross, B., & Neuberger, C. (2018). Social media analytics – Challenges in topic discovery, data collection, and data preparation. International Journal of Information Management, 39, 156–168. https://doi.org/10.1016/j.ijinfomgt.2017.12.002

Taboada, M., Brooke, J., Tofiloski, M., Voll, K., & Stede, M. (2011). Lexicon-Based Methods for Sentiment Analysis. Computational Linguistics, 37(2), 267–307. https://doi.org/10.1162/COLI_a_00049

Torpan, S., Hansson, S., Rhinard, M., Kazemekaityte, A., Jukarainen, P., Meyer, S. F., Schieffelers, A., Lovasz, G., & Orru, K. (2021). Handling false information in emergency management: A cross-national comparative study of European practices. International Journal of Disaster Risk Reduction, 57, 102151. https://doi.org/10.1016/j.ijdrr.2021.102151

Veil, S. R., Buehner, T., & Palenchar, M. J. (2011). A Work□In□Process Literature Review: Incorporating Social Media in Risk and Crisis Communication. Journal of Contingencies and Crisis Management, 19(2), 110–122. https://doi.org/10.1111/j.1468-5973.2011.00639.x

Vieweg, S., Hughes, A. L., Starbird, K., & Palen, L. (2010). Microblogging during two natural hazards events: What twitter may contribute to situational awareness. Proceedings of the SIGCHI Conference on

Human Factors in Computing Systems, 1079–1088. https://doi.org/10.1145/1753326.1753486
Vos, S. C., & Buckner, M. M. (2016). Social Media Messages in an Emerging Health Crisis: Tweeting Bird Flu. Journal of Health Communication, 21(3), 301–308. https://doi.org/10.1080/10810730.2015.1064495
Wong-Villacres, M., Velasquez, C. M., & Kumar, N. (2017). Social Media for Earthquake Response: Unpacking its Limitations with Care. Proceedings of the ACM on Human-Computer Interaction, 1(CSCW), 1–22. https://doi.org/10.1145/3134747
Zhai, W., Yu, H., & Song, C. Y. (2023). Disaster Misinformation and Its Corrections on Social Media: Spatiotemporal Proximity, Social Network, and Sentiment Contagion. Annals of the American Association of Geographers, 114, 408–435. https://doi.org/10.1080/24694452.2023.2271549
Zook, M., Graham, M., Shelton, T., & Gorman, S. (2010). Volunteered Geographic Information and Crowdsourcing Disaster Relief: A Case Study of the Haitian Earthquake. World Medical & Health Policy, 2(2), 7–33. https://doi.org/10.2202/1948-4682.1069