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Application of Social Media Data to Enhance the Performance of Humanitarian Logistics: A Case Study of Vietnam in the Aftermath of Typhoon Yagi

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Abstract: In recent years, humanitarian logistics have received much attention from practitioners and researchers due to the significant damage from natural disasters on a global scale. This case study investigated the potential of leveraging social media data to enhance the effectiveness of humanitarian logistics in Vietnam after the disaster caused by Typhoon Yagi. The research examined public sentiment about the disaster response efforts, pinpointed the needs of critical relief, and assessed the performance of various machine learning models in classifying disaster-related content on social media. Data was sourced from multiple platforms, preprocessed and then categorized according to the damage types, required relief supplies, and sentiment labels. After that, different machine learning models were utilized to analyze the negative impact of the disaster. The analysis revealed that housing and transportation were the primary sources of negative public sentiment, indicating significant unmet needs in these areas. In contrast, generally more positive responses were received in relation to cash assistance, food, and medical support. A comparative evaluation of 12 machine learning models suggested that conventional algorithms, such as Random Forest, Support Vector Machine, and Logistic Regression, outperformed deep learning models in sentiment classification tasks. These findings shed light on the value of social media as a real-time indicator of public perception and logistical effectiveness. Therefore, incorporating sentiment analysis into the planning of disaster response can support more adaptive, timely, and community-informed decision-making for governments and humanitarian organizations.

Keywords: Disaster recovery; Humanitarian logistics; Sentiment analysis; Social media; Typhoon Yagi in Vietnam

1. Introduction

In recent years, the world has witnessed a marked escalation in both the severity and frequency of natural disasters, ranging from floods, storms, and droughts to pandemics, thus posing formidable challenges to socio-economic development (Botzen et al., 2019). For instance, in July 2021, Western Europe experienced catastrophic flooding following record rainfall, with Germany and Belgium among the hardest-hit countries. In Germany alone, over 100 people lost their lives while thousands were displaced; the economic cost was estimated to be over €30 billion (Odersky & Löffler, 2023), hence one of the costliest natural disasters in the country's postwar history. Later that same year, in August 2021, a powerful 7.2 magnitude earthquake struck southwestern Haiti, resulting in over 2,200 deaths and injuring more than 12,000 people. The quake destroyed or damaged tens of thousands of homes, schools, and healthcare facilities, compounding the country's ongoing humanitarian crisis and causing an estimated US$1.6 billion in damages (Pan American Health Organization, 2021).

In the face of such crises, humanitarian logistics emerged as a pivotal component of disaster management, to enhance the efficiency of relief operations and mitigate the detrimental effects of disasters (Sahay et al., 2016). During the COVID-19 pandemic, for example, deficiencies in logistics systems led to critical challenges such as shortages of medical staff, scarcity of personal protective equipment, and limited capacity in intensive care units and hospital wards (Alghamdi & Alghamdi, 2022). Despite the substantial involvement of volunteers and crowdsourcing during Typhoon Yagi, a stark imbalance in supply and demand across various locations underscored the consequences of inadequate coordination with humanitarian organizations and the absence of fundamental training (Tran Tran, 2024). These cases underscored the indispensable role of humanitarian logistics, which account for 60 to 80 percent of the total expenditures on humanitarian relief (Lacourt & Radosta, 2019), in supporting the disaster response efforts of governments, humanitarian agencies, and voluntary participants alike.

According to Kembro et al. (2024), humanitarian logistics was defined as "the logistics and supply chain management focusing on the preparation for, response to, and recovery from a humanitarian crisis, with the aim of saving lives and alleviating the suffering of affected populations". Humanitarian operations are typically structured around four distinct phases, to align with the life cycle of a disaster: mitigation, preparedness, response, and recovery (Çelik et al., 2012). While much of the existing literature has concentrated on applying supply chain methodologies to enhance the efficiency of disaster response efforts, there remains a significant gap in research concerning humanitarian development and its role in mitigating future disaster impacts. Recent reviews in the field have further underscored this shortfall, thus emphasizing the need for deeper exploration of the recovery phase in disaster management (Mohammadi et al., 2024; Wolbers et al., 2021). The critical importance of the recovery phase was also affirmed by Masudin & Fernanda (2019), who asserted that effective recovery from a disaster was instrumental in ensuring the long-term survival and resilience of the affected population.

Çelik et al. (2012) defined the fourth phase of disaster management, i.e., recovery, as encompassing long-term activities after the immediate effects of a disaster have subsided. This stage focuses on restoring communities and infrastructure to a state of normalcy and resilience. In recent years, a range of emerging technologies has been explored to enhance both disaster response and recovery efforts, including Internet-of-Things, blockchain, big data, artificial intelligence, 3D printing, and virtual or augmented reality (Argumedo-García et al., 2021; Khan et al., 2021; Schumann-Bölsche, 2017). Additionally, intelligent systems that integrate multi-source information have demonstrated potential in supporting decision-making processes during disaster management (Fallucchi & De Luca, 2016). For instance, the study by Gruebner et al. (2018) utilized data from Twitter to identify expressions of negative emotions in New York City before, during, and after Superstorm Sandy in 2012. Their findings revealed a spike in negative sentiment following the storm, surpassing emotional distress levels observed during the disaster itself. This insight underscores the value of social media as a real-time and community-level indicator of recovery needs, thus helping to pinpoint areas and populations most in need of targeted care and intervention. Despite the growing digital landscape, there remains a critical need for further research into the application of social media data in community recovery, particularly in understanding how such data correlates with tangible and on-the-ground recovery activities (Shibuya, 2017).

Recent studies have increasingly explored the application of social media data and sentiment analysis in the field of humanitarian logistics. Zhang et al. (2024) utilized climate change-related posts on the social media during extreme typhoon events in China to conduct a national-level analysis, aiming to heighten public awareness of climate change and thereby preparing for relevant solutions. Similarly, Khusna et al. (2023) employed Twitter data from Indonesia to evaluate the resilience of the nation when facing natural disasters, thus generating insights to support more effective disaster management strategies proposed by the government, humanitarian organizations, and local communities.

Vietnam is among the most disaster-prone countries in Asia (ADRC, 2022), being placed 15th in the list of countries at the most risk of natural disasters globally in 2023 (VNS, 2022). According to the United Nations Office for Disaster Risk Reduction (UNDRR) (2022) and the Ministry of Agriculture and Rural Development in Vietnam, with a coastline of 3,300 km, the country is exposed to hydro-meteorological hazards such as storms, floods, landslides, drought, salt-water intrusion, and coastal erosion (ADRC, 2022). However, Vietnam has received comparatively little scholarly attention in the domain of humanitarian logistics in general and in applying social media data to boost the performance of disaster management. In response to this gap, our study investigated the case of Typhoon Yagi in 2024 by:

(1) conducting sentiment analysis of public opinions regarding disaster response, quantifying the distribution of positive and negative sentiments;
(2) analyzing essential relief needs identified by victims during the disaster response phase; and
(3) exploring and comparing the performance of various machine learning models in classifying disaster-related social media data.

The remainder of this article was structured as follows. Section 2 presented a comprehensive literature review. Section 3 detailed the case of Typhoon Yagi, which struck Vietnam from September 6 to 10, 2024 and outlined the construction of the associated social media dataset. Section 4 discussed the empirical results, including classifications of physical damage, emotional impact, and relief needs. Section 5 provided an in-depth discussion of the findings, while Section 6 concluded the study.

2. Literature Review

2.1 Humanitarian Logistics in the Recovery Phase of Disaster Management

Humanitarian logistics plays a pivotal role in disaster management, particularly during the recovery phase. It encompasses the mobilization of resources, expertise, and strategic knowledge to support vulnerable populations affected by disasters (Gupta, 2016). The effectiveness of relief efforts is intrinsically linked to the quality of humanitarian logistics, with key stakeholders such as governments and relief organizations assuming critical responsibilities in the immediate aftermath of a disaster (Shokr et al., 2022) as well as the transparency in humanitarian logistics (Khan et al., 2019). Furthermore, Van Krieken & Pathirage (2019) emphasized that the efficiency and timeliness of logistics operations during the recovery phase significantly influenced the capacity of the local community to rebuild. Platt (2017) reinforced this by asserting that effective post-disaster decision-making processes directly impacted both the pace and quality of recovery. Notably, the development of intelligent decision-making frameworks offered promising solutions to the inherent challenges of disaster management, such as identification of survivors and distribution of relief supplies (Chaudhuri & Bose, 2020). A deep learning model was proposed to enhance the operational efficiency of humanitarian organizations by predicting the locations of distribution centers, demand and efficient distribution of relief (Tanti et al., 2023). Therefore, this paper aims to propose a potential solution to improve post-disaster decision-making processes and support more resilient recovery strategies.

2.2 Application of Social Media Data in Post-Disaster Recovery

Researchers have devised methodologies to analyze vast volumes of social media data, thus enabling the identification and classification of damage reports from affected individuals, the assessment of key discussion topics, and a deeper understanding of recovery decisions (Jamali et al., 2019; Jamali et al., 2020). These studies suggested that communities exhibiting higher levels of socially interactive tweets were more inclined to engage in post-disaster reconstruction efforts (Jamali et al., 2020). While much of the existing literature has concentrated on disaster mitigation and immediate response, there remains a pressing need to explore the role of social media in facilitating long-term community recovery (Shibuya, 2017). Active users of social media platforms frequently participate in ground-level recovery operations, effectively bridging the gap between digital discourse and physical action (Tim et al., 2017).

Moreover, social media has proven instrumental in aiding governments and humanitarian agencies in aligning the supply of resources with the dynamic demand across affected locations. Wong et al. (2018) highlighted that the integration of social media into the frameworks of emergency logistics significantly enhanced the decision-making processes of disaster management authorities. To this end, automated tools have been developed to extract, analyze, and visualize actionable insights from user-generated content, thereby supporting coordinated relief efforts (Nazer et al., 2017). For instance, Tan & Schultz (2021) utilized Weibo data to generate real-time assessments of damage and recovery conditions, in order to inform regional flood mitigation strategies and promote sustainable redevelopment of impacted areas. Similarly, Dong et al. (2021) employed Twitter data to explore how information sharing could guide relief agencies to better understand the need of essential supplies during disasters.

However, most of these studies have relied exclusively on a single social media platform, such as Twitter (X), Weibo, or Facebook, thereby exposing to biased or incomplete perspectives due to the limited scope of data sources. To overcome this limitation, the present study endeavored to integrate data from multiple platforms, so as to offer a comprehensive and balanced view of disaster impacts and recovery dynamics.

2.3 Application of Sentiment Analysis in Post-Disaster Recovery

Sentiment analysis of social media data has emerged as a powerful tool for evaluating post-disaster recovery and enhancing disaster management strategies. It enables the categorization of disaster-related content based on the needs and emotional states of affected individuals, thereby assisting emergency responders in formulating more effective information management protocols (Ragini et al., 2018). By facilitating real-time monitoring of public sentiment, sentiment analysis significantly contributes to situational awareness and crisis response efforts (Kanungo & Jain, 2023). Furthermore, when integrated with text mining techniques, it allows the automatic identification of interconnected events, such as disaster impacts, recovery measures, and public feedback, in order to offer valuable insights for strategic planning and resource allocation in future emergencies (Anam et al., 2019; Thomas et al., 2019).

With the advent of Industry 4.0 technologies, machine learning-based sentiment analysis has seen rapid advancement (Monika et al., 2022). This method enables dynamic and real-time analysis of public sentiment during and following disasters, thereby empowering emergency agencies to devise more responsive and data-driven strategies (Dong et al., 2020). Given that supervised machine learning techniques generally outperform unsupervised methods in classification tasks (Pan & Yang, 2010), this study adopted a suite of supervised learning models for sentiment classification. For instance, Wahid et al. (2022) introduced a structured supervised learning framework capable of detecting potential crises signaled by victims' negative emotional expressions in the aftermath of disasters.

However, previous research predominantly focused on English-language datasets. In contrast, this study leveraged social media content in Vietnamese language, to offer a comparative analysis of various supervised machine learning models tailored to the linguistic and contextual characteristics of the dataset.

Building upon insights from prior research, this study seeks to strengthen post-disaster decision-making and foster resilient recovery by proposing a comprehensive framework that synthesizes data from multiple social media platforms. By addressing notable limitations in existing literature, particularly the dependence on single-platform analyses and English-language datasets, this paper distinguished itself as it focused on Vietnamese-language content. Furthermore, it offered a context-sensitive evaluation by comparing the performance of various supervised machine learning models, ultimately contributing to a more nuanced and inclusive perspective to disaster response strategies.

3. Methodology

The framework and methodology presented in this study are illustrated schematically in Figure 1, covering four main stages: gathering relevant raw data from various social media platforms based on the disaster, typhoon Yagi; conducting data preprocessing and its subsequent analysis; finally, applying sentiment analysis using different machine learning techniques. Through this structured approach, the framework aims to extract critical insights from social media content and demonstrate the potential of such data in enhancing crisis management strategies, in order to improve the effectiveness of disaster response.

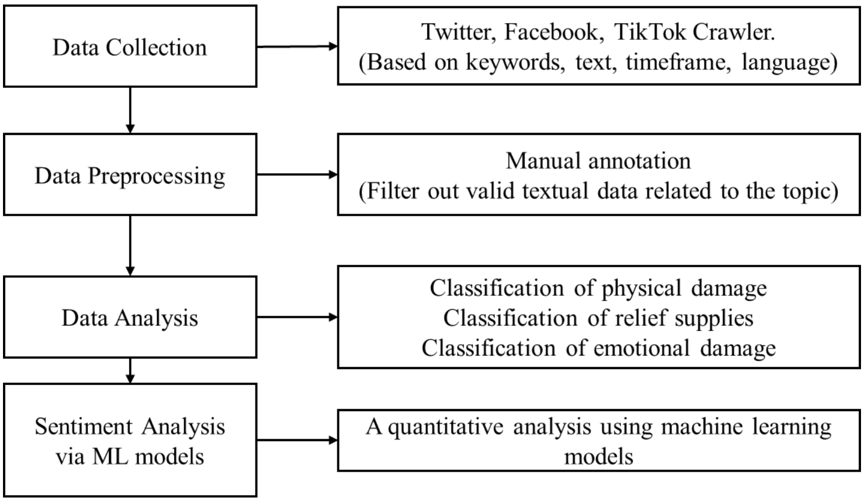

Figure 1. Framework of the study

3.1 Data Collection

In this research, three websites were chosen for the collection of data, i.e., Twitter (X), Facebook, and TikTok, as they are the three most popular microblogs in Vietnam with over 50 million users, along with millions of posts updated each day. Apify's tools were used to retrieve the content of Twitter, Facebook, and TikTok by adapting Twitter Search Scraper, Facebook Posts Search Scraper, and TikTok Scraper, respectively. A total of 6,488 texts have been extracted as they covered the topic of Typhoon Yagi. The data were collected in the specified time frame from 01/09/2024 to 01/10/2024. Examples of keywords and hashtags used for data collection are listed in Table 1.

3.2 Data Preprocessing

First, we pooled the collected data from Twitter, Facebook, and TikTok to capture a holistic view of public discourse, which was essential for understanding the overall challenges of humanitarian logistics during Typhoon Yagi. Next, we extracted effective social media data specific to the research topic; a total of 5,916 texts were eliminated due to irrelevant information, thus leading to 527 texts for the final dataset. We applied the following predefined filtering criteria to ensure the reliability of input data for analysis and machine learning: (i) removal of duplicates; (ii) exclusion of irrelevant posts (e.g., personal reflections and unrelated advertisements); and (iii) exclusion of posts with insufficient content (posts that contained icons, hashtags, and irrelevant languages; re-sharing from other posts; and lack of geolocation or temporal information).

Table 1. Keywords and hashtags used for data collection

Social Media	Keywords	Hashtags
Twitter (X) Facebook TikTok	Yagi; Bão Yagi; Yagi Vietnam; Yagi Việt Nam; Yagi Vietnam Supply; cứu trợ yagi việt nam; thiên tai yagi; thiệt hại yagi	#yagi #yagityphoon #baoso3 #baoyagi

Note: Disaster: Typhoon Yagi; Timeframe: 01/09/2024 – 01/10/2024; Language: Vietnamese

3.3 Qualitative Analysis

Following the data preprocessing phase, we manually classified the dataset into three distinct categories: types of damage, relief supplies, and emotional sentiment.

First, drawing on the classification framework proposed in the research of Tan & Schultz (2021), this study categorized damage into five primary groups: (1) affected individuals; (2) disruptions to economically productive activities; (3) damaged houses or buildings; (4) lost personal property; and (5) damaged infrastructure. For example, texts containing keywords such as “traffic jams”, “delays”, and “road closures” were associated with the “damaged infrastructure” category in the dictionary of physical damages. Second, the relief supplies category was divided into five-standard group housing, transportation, medical aid, and food, in accordance with Dong et al. (2021). In the context of Typhoon Yagi in Vietnam, a notable amount of support came in the form of financial donations. This study introduced the fifth category, “cash”, to better capture the diversity of relief types observed. We did manual classification of the five damage types, including cash, food, housing, medicine, and transportation. Lastly, based on the effectiveness of relief efforts provided by governmental bodies, humanitarian organizations, or individual volunteers, social media posts were classified into positive or negative sentiment categories. This classification reflects public perception of the adequacy and timeliness of relief distribution and support. We established a predefined classification guidelines for adding annotations together and crosschecking to ensure consistency and inter-annotator reliability.

3.4 Sentiment Analysis

A quantitative analysis was undertaken to equip decision-makers with an automated tool for examining disaster-related social media data and addressing the research problem. Specifically, this study applied 12 machine learning models to classify public sentiment in disaster-relevant social media posts and compared the performance of these models in terms of both computational efficiency and predictive accuracy. The findings of this research enabled emergency response managers to promptly identify victims’ needs and allocate relief resources more effectively, thereby enhancing the overall efficiency of disaster response efforts.

4. Results

4.1 Qualitative Analysis of Sentimental Tweets

4.1.1 Determination and analysis of sentimental data

The classification of positive and negative sentiments can vary significantly depending on the subject matter and the perspective from which it is viewed. In this study, however, we focused exclusively on sentiments relating to the effectiveness of disaster response efforts. Drawing on the approach from Dong et al. (2021), we defined sentiment categorization based on the perceived performance of government bodies and relief agencies during disaster response. Specifically, tweets that reflect positively on the actions or impact of these entities are labeled as positive sentiments, whereas tweets highlighting shortcomings, criticism, or dissatisfaction are categorized as negative sentiments. Table 2 provides illustrative examples of these sentiment labels. For the purpose of classification, positive sentiments are assigned the label 0, while negative sentiments are assigned the label 1.

Figures 2 and 3 illustrate the temporal dynamics of public sentiment on social media in response to Typhoon Yagi in Vietnam. In the initial stage, notably around September 6 to 9, negative emotions dominated the discourse, with the peak of negative sentiment occurring on September 8, thus reflecting public concern over the severity of the typhoon. Expressions of anxiety and frustration were prevalent, likely driven by disruptions to transportation, infrastructure, and daily life caused by the storm. However, as time progressed, a notable shift occurred. From mid-September onward, the texts of positive sentiments gradually increased, surpassing negative ones on several days. This change in tone could be attributed to growing public appreciation for the response efforts and the resilience shown by affected communities. Social media posts expressing encouragement, solidarity, and gratitude, such as “Ấm lòng quá”, “Ấm lòng hành động của bác tài”, “các anh bộ đội hỗ trợ bà con khắc phục bão lũ” highlighted collective optimism and determination to overcome the disaster. Thus, the sentiment evolution suggests an emotional transition from initial distress to hope and unity in the face of adversity.

Table 2. Categories of sentiments

Text (X)	Label (Y)
“Hoan hô tình đồng bào giữu cơn bão: Mọi người cùng giúp đỡ che chắn, đẩy xe qua đường”	Positive (0)
“Cập nhật lúc này tại Quảng Ninh - Bão Yagi thổi nhà tốc hết mái. Khổ quá mong bão mau qua đi”	Negative (1)

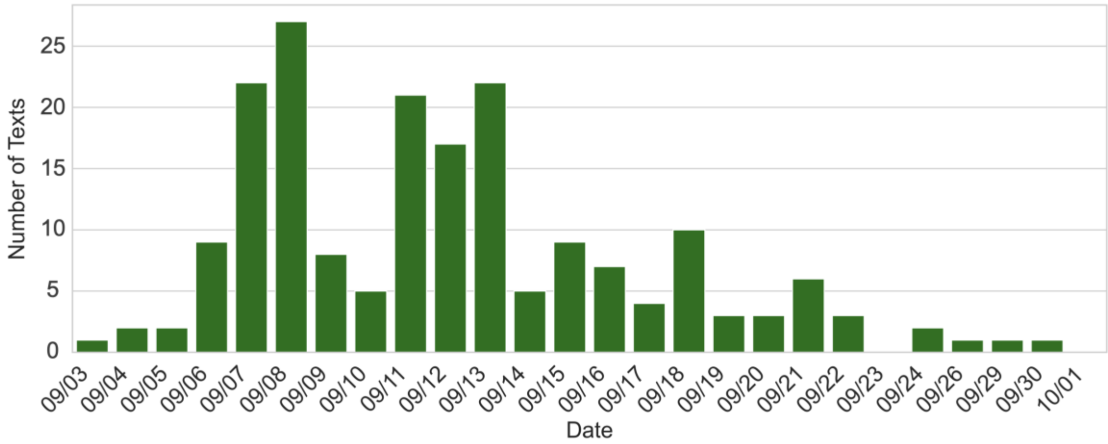

Figure 2. Number of positive texts recorded by time

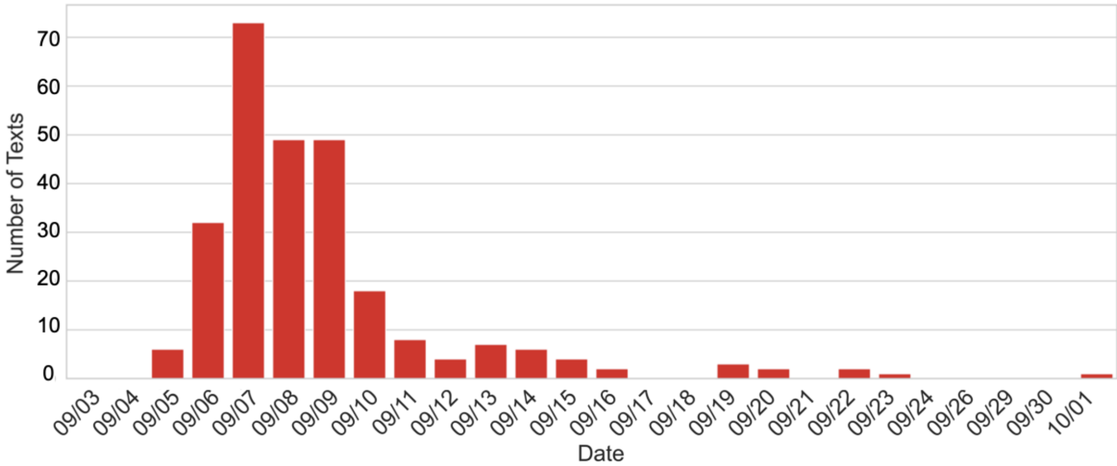

Figure 3. Number of negative texts recorded by time

4.1.2. Analysis of different types of damage

As shown in Figure 4, the physical damage caused by Typhoon Yagi in Vietnam was classified into five categories: affected people, economic impact, housing damage, lost property, and infrastructure issues. Based on the frequency of reports, damage to houses and buildings was the dominant topic, with affected people and infrastructure ranking second and third, respectively. This high volume of mentions suggested that these were the most pressing issues, potentially correlating with the intensity of the disaster in central areas. In contrast, the data showed minimal focus on economic activities and property loss, with mentions never exceeding 10 texts at any point.

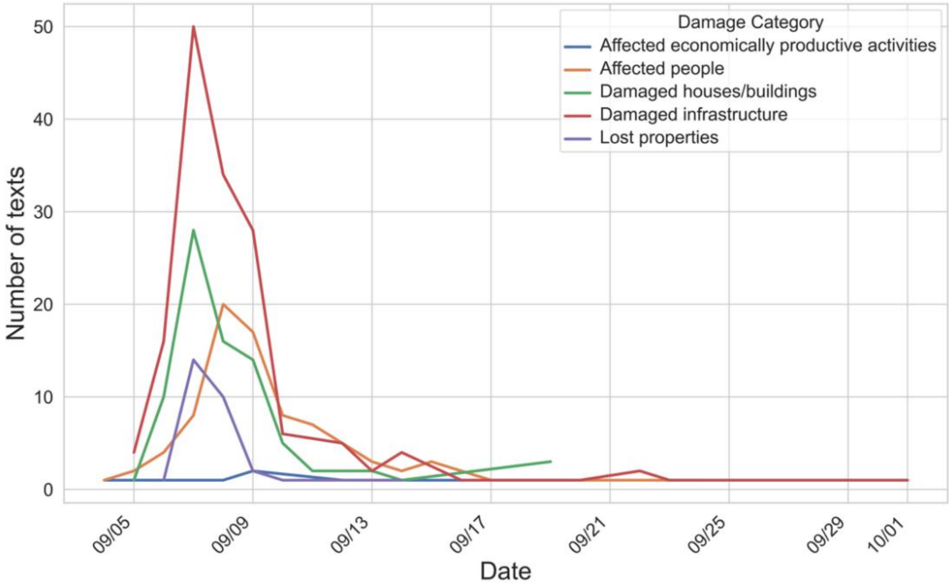

Figure 4. Frequency of texts by damage type

4.1.3. Analysis of the identical type of relief supplies

In this phase, we examined the sentiment distribution of tweets concerning various essential relief supplies to gain deeper insights into public concerns. As illustrated in Figure 5, housing and transportation received the highest amount of negative sentiment, indicating substantial dissatisfaction or critically unmet needs in these domains during the disaster. This revealed that shelter and mobility were the most urgent priorities for affected communities. Accordingly, humanitarian organizations should emphasize the provision of emergency housing and robust transport logistics in their response frameworks. Conversely, the comparatively higher proportion of positive tweets regarding cash, food, and medical assistance suggested a more favorable public perception or adequate fulfillment of these needs. The pronounced negative sentiment surrounding transportation further underscores the necessity for enhanced evacuation infrastructure, thus reaffirming the vital importance of comprehensive transport planning in Vietnam with disaster preparedness and related mitigation efforts.

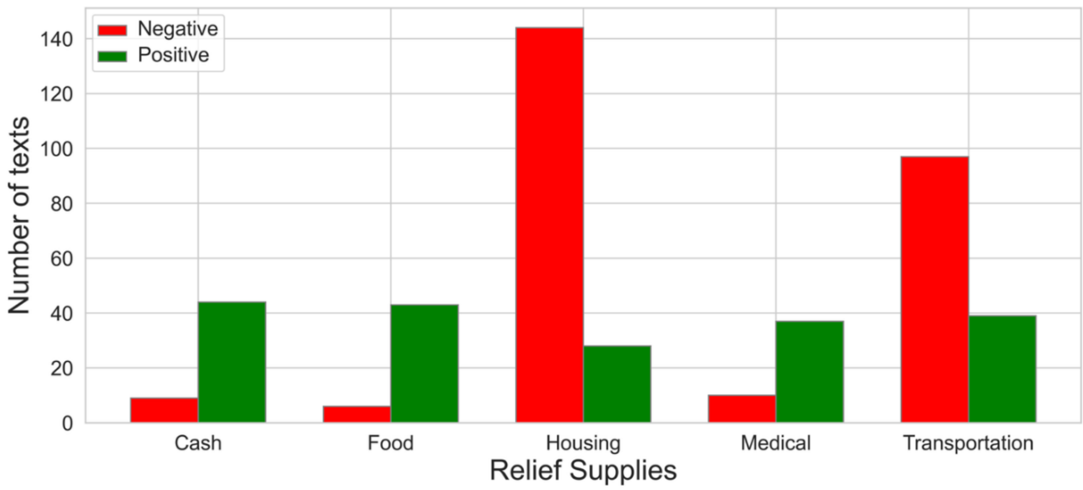

Figure 5. Sentiment distribution by relief supply

According to Figures 6–10, the sentiment analysis of social media data following Typhoon Yagi in Vietnam provided critical insights into public perceptions and response patterns across core humanitarian logistics sectors, i.e., cash, transportation, food, housing, and medicine during the post-disaster phase. Cumulative sentiment trajectories indicated that cash and food categories experienced a strong rise in positive mentions with limited negative sentiments, implying relatively efficient financial aid distribution and successful food relief operations. In contrast, the transportation and housing sectors showed a significant accumulation of negative sentiments over the course of time, arising from prolonged infrastructure damage, mobility restrictions, shelter insecurity, and areas demanding prioritized logistical intervention. Notably, the medical sector displayed a consistent increase in positive sentiment with minimal negativity, suggesting that healthcare services were relatively accessible and well-coordinated during the recovery process. These results demonstrated how social media data could reveal granular and real-time feedback on logistical performance, allowing humanitarian actors to identify both effective interventions and persistent gaps. Thus, integrating such sentiment-based analytics into post-disaster logistics planning could enhance situational awareness, resource prioritization, and adaptive response, thereby improving resilience in future disaster scenarios.

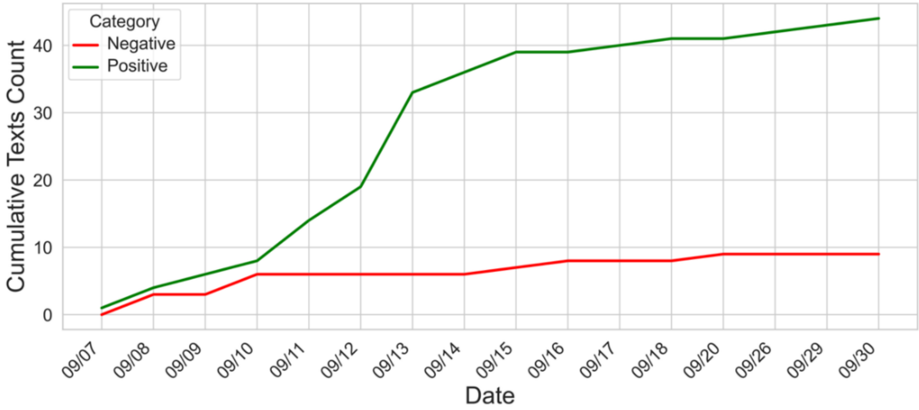

Figure 6. Sentiment distribution over time–cash

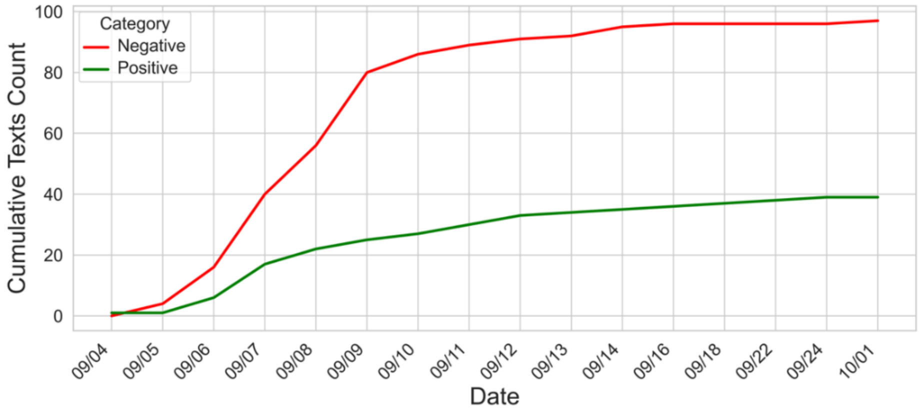

Figure 7. Sentiment distribution over time–transportation

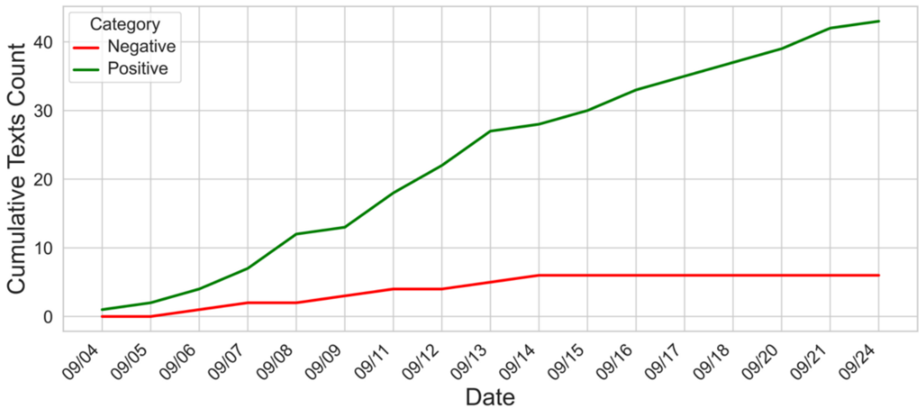

Figure 8. Sentiment distribution over time–food

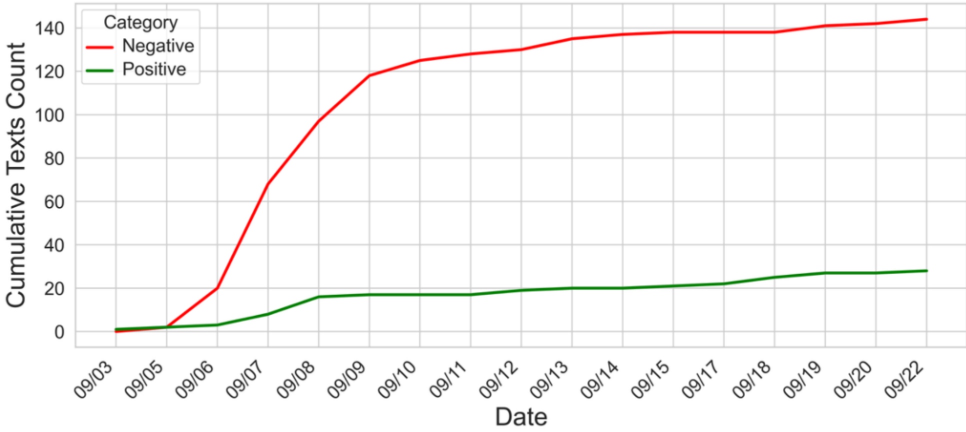

Figure 9. Sentiment distribution over time–housing

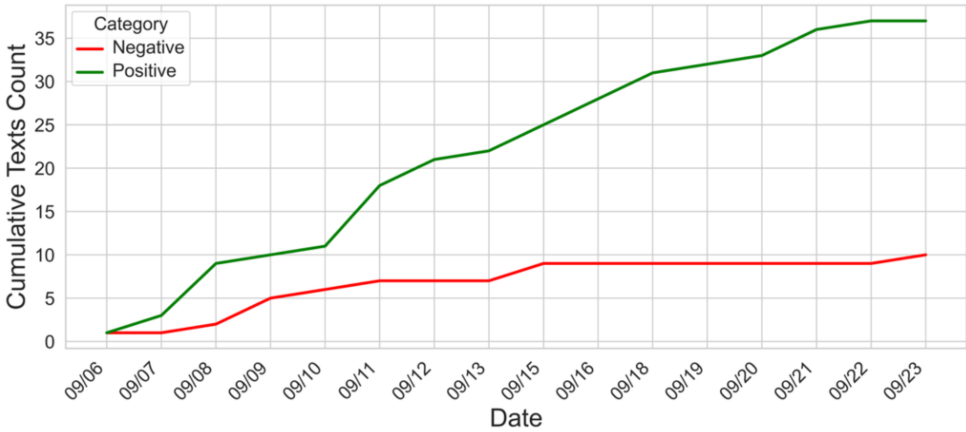

Figure 10. Sentiment distribution over time–medicine

4.2 Quantitative Analysis with Machine Learning Models

In this phase, we applied various machine learning models to perform sentiment analysis. The workflow comprised five primary stages: data collection, data preprocessing, learning, evaluation, and prediction, as illustrated in Figure 11. While the data collection process was reported in the preceding section, subsequent tasks are presented in the following discussion.

4.2.1 Data preprocessing

Data cleaning

The quality of a dataset plays a crucial role in determining the effective performance of a machine learning model. Therefore, it is essential to thoroughly examine and preprocess the dataset before feeding it into a learning model. Typically, raw social media data contains HTML markup, punctuation, emojis, and other special characters. For simplicity and clarity, this study removed all punctuation marks, hyperlinks, and irrelevant content from the raw data with Python's regular expression (regex) library.

Following this, the cleaned text was tokenized and split into individual words to enable further preprocessing steps. These included converting all texts to lowercase, stemming or lemmatizing words to their root forms, and eliminating stop-words, redundant characters, and informal language commonly known as "teen code". Stop-words are frequent terms that usually carry little discriminative value for classification tasks, such as "là", "và", "có", and "như". To address this, the Vietnamese Stop-words Dash dataset from Kaggle was employed.

Teen code, characterized by informal, abbreviated, or stylized expressions such as "haizz", "hic", "LOL", and "hông" used mainly by younger demographics, was manually normalized. The meanings of these terms were collected and adjusted in the dataset to ensure semantic consistency and enhance model interpretability.

Feature vector

Categorical data, such as texts or words, must be converted into numerical form before it can be processed by a machine learning model. In this research, we employed widely used techniques known as Term Frequency-Inverse Document Frequency (TF-IDF) and pre-trained language models for Vietnamese, PhoBERT, to transform textual data into numerical feature vectors.

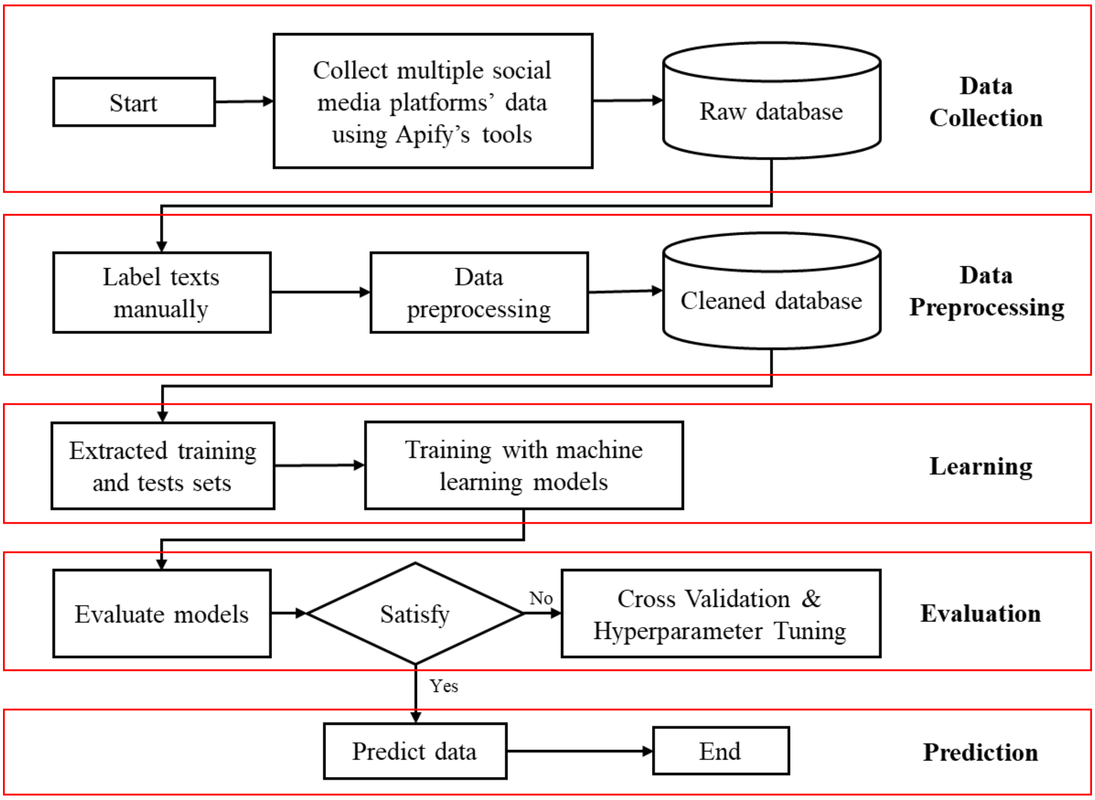

Figure 11. Workflow of machine learning models for sentiment analysis

4.2.2. Learning

Supervised learning was employed in this study, as all machine learning models were trained on discretely labeled data. The primary objective of this research is to investigate the potential role of social media in natural disaster relief by predicting users' sentiments, whether positive or negative, which constitute a classification task. To evaluate and compare model performance, we utilized eight widely recognized machine learning algorithms consistent with those used in Dong et al. (2021). These were Logistic Regression (LR), Naïve Bayes (NB), Decision Tree (DT), Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Random Forests (RF), AdaBoost, and Multilayer Neural Network (MNN). To enhance the comprehensiveness of our model comparison, we further extended the study by incorporating four deep learning models: Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Gated Recurrent Unit (GRU), and Bidirectional LSTM (BI-LSTM).

We divided the entire dataset into two subsets: a training set and a testing set. The training set comprised 70% of the total data, while the remaining 30% was allocated to the testing set. As illustrated in Table 2, each text entry in the dataset contains two features: X, representing the textual content, and Y, denoting the sentiment label associated with the tweet. In this learning task, we focused on these two features. The values of X and Y were then used as inputs for various machine learning models during the training phase.

4.2.3. Model evaluation

This study employed the GridSearchCV method to identify the optimal set of hyperparameters for the training models through fivefold stratified cross-validation. GridSearchCV systematically selects parameter values that maximize model accuracy, while cross-validation ensures the model is trained and tested on distinct subsets of data for robust performance evaluation. Model evaluation is essential, as it enables more effective utilization of the dataset and offers deeper insights into the predictive capabilities of the algorithm. Moreover, this approach serves as a safeguard against underfitting and overfitting, to ensure the generalizability of the model. For instance, Decision Tree classification involves parameters such as the maximum depth of the tree, the minimum number of samples required to split an internal node, and the criterion used to measure the quality of a split (e.g., Gini impurity or entropy). Manually identifying the optimal combination of these parameters is challenging; however, GridSearchCV automates this process, enabling the construction of models with complex transformation pipelines and facilitating the accurate classification of new data.

4.2.4. Prediction

Data resulting from the cleaning phase was fed into the machine learning algorithms. These models were then fine-tuned using various evaluation strategies. As illustrated in Table 3, the confusion matrix depicted in Figure

12 was employed to evaluate the accuracy of the prediction outcomes. This matrix visualizes the performance of a classification model by organizing predictions into counts of true positive (TP), true negative (TN), false positive (FP), and false negative (FN).

Table 3. Classification metrics

Label	P	R	F1	P	R	F1
		Naïve Bayes			Logistics Regression	
Positive	0.91	0.84	0.88	0.92	0.88	0.90
Negative	0.90	0.95	0.93	0.93	0.95	0.94
			0.91*			0.92*
		Decision Tree			SVM	
Positive	0.95	0.80	0.87	0.92	0.88	0.90
Negative	0.89	0.98	0.93	0.93	0.95	0.94
			0.91*			0.92*
		KNN			Random Forest	
Positive	0.80	0.88	0.82	0.91	0.84	0.88
Negative	0.90	0.84	0.89	0.91	0.95	0.93
			0.86*			0.91*
		AdaBoost			MNN	
Positive	0.81	0.84	0.82	0.88	0.88	0.88
Negative	0.90	0.88	0.89	0.93	0.93	0.93
			0.86*			0.91*
		RNN			LSTM	
Positive	0.42	0.91	0.46	0.50	0.04	0.08
Negative	0.87	0.31	0.58	0.65	0.98	0.78
			0.81*			0.65*
		GRU			BI-LSTM	
Positive	0.50	0.04	0.08	0.82	0.39	0.53
Negative	0.65	0.98	0.78	0.74	0.95	0.83
			0.65*			0.75*

Note: *The accuracy score of the model

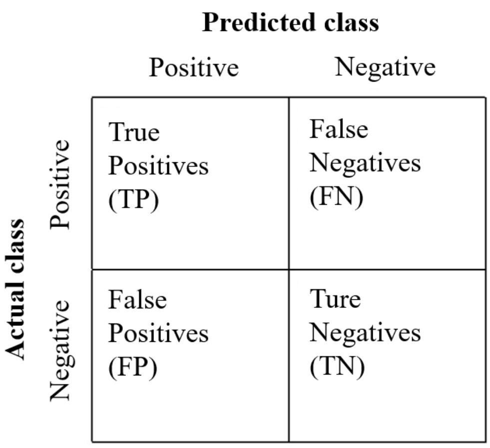

Figure 12. Confusion matrix

Four key indicators derived from the confusion matrix were adopted to assess model performance. First, Accuracy (ACC) provides a general overview of correct predictions. Second, Precision (PRE) determines the relevance of the data identified by the model. Third, Recall (REC) measures the ability of the model to retrieve all relevant texts. Lastly, we calculated the F1-score (F1), which acts as the harmonic mean of PRE and REC to balance these metrics.

4.2.5. Evaluation of machine learning models

To effectively classify sentiment from social media data in the context of post-disaster humanitarian logistics, various machine learning models, including traditional classifiers and deep learning approaches, were evaluated in Table 3. The results demonstrated that traditional machine learning models, particularly Random Forest, Logistic Regression, and SVM, outperformed deep learning architectures in terms of both precision and recall. Random Forest achieved the highest accuracy score (0.91), with balanced F1-scores for both positive (0.88) and negative (0.93) sentiments. Similarly, SVM and Logistic Regression also exhibited strong and consistent performance of 0.92 and 0.9 accuracy scores, respectively, indicating their robustness in handling relatively small and structured textual datasets. On the contrary, deep learning models such as RNN, LSTM, GRU, and BI-LSTM underperformed significantly, particularly on positive sentiment classification, with accuracy scores ranging from 0.65 to 0.81. This may be attributed to limited data volume or insufficient sequence learning due to short and informal social media texts. Notably, Naïve Bayes and Decision Tree models maintained competitive scores but slightly lagged behind ensemble methods and SVM in generalization.

These findings suggested that for short-text sentiment classification in the contexts of disasters, traditional machine learning methods, especially ensemble and margin-based models, might provide more reliable performance than deep learning approaches without extensive training data or advanced pretraining techniques. While Kumar et al. (2019) asserted that deep neural networks might show promising results in some cases, ensemble methods like voting classifiers demonstrated more competitive performance and computational efficiency (Chabane et al., 2024). Additionally, traditional models such as Random Forest and Support Vector Machines have achieved accuracy comparable to Bidirectional Encoder Representations from Transformers (BERT) in disaster tweet classification (Chabane et al., 2024). Besides, the effectiveness of different approaches may depend on the specific dataset and task, with some studies reported that ensemble deep learning models performed best for certain sentiment classification tasks (Kamruzzaman et al., 2021).

5. Discussion

Leveraging the strengths of social media data allows researchers to better access information from affected individuals during crises, thus marking a significant shift in the era of big data. By analyzing user-generated content across multiple platforms, e.g., Facebook, Twitter (X), and TikTok, this research identified not only the emotional trajectory of affected populations but also their priority of relief needs. For instance, Gour et al. (2022) adapted user-generated content on social media to identify the emotional trajectory and optimized resources and relief packages in the right direction proactively during a disease outbreak. Most notably, housing and transportation emerged as dominant areas of dissatisfaction, as indicated by a high amount of negative sentiment, whereas financial assistance, food, and medical support were generally perceived to be more positive. Besides, topic modeling and content analysis of social media posts have been used to examine victims' priorities over the course of time, with housing and relief goods identified as top concerns (Malawani et al., 2020). Thus, our findings suggested that public sentiment was a reliable proxy for identifying operational gaps and successes in disaster response.

Comparative evaluation of the performance of 12 machine learning models revealed that traditional supervised learning approaches such as Random Forest, Support Vector Machine, and Logistic Regression outperformed deep learning models in sentiment classification tasks involving short, informal, and Vietnamese-language texts. As discussed in section 4.2.5, our results highlight the practicality and efficiency of traditional models in disaster-related sentiment analysis, especially in low-resource language settings.

Some limitations remain in the use of social media data for disaster analysis. Posts may include false or exaggerated information, and many victims may not express their experiences online, leading to incomplete or biased insights. Additionally, emotional distress is difficult to verify through sentiment analysis alone. To address these challenges, future research should consider combining social media data with remote sensing, online or field surveys, and official reports. This multimodal approach could enhance the reliability of findings and provide a thorough understanding of disaster impacts and community needs.

6. Conclusions

Disasters often inflict profound and multifaceted costs on affected regions, including substantial financial losses, ecological degradation, infrastructural destruction, and tragic loss of life. These consequences significantly impede the progress of regional development and disrupt environmental stability. As such, mitigating the impact of disasters is a critical prerequisite for achieving sustainable regional development. This study employed the case study of Typhoon Yagi in Vietnam to explore the potential of social media data-driven analytics in enhancing the efficiency of disaster response, with a particular focus on analyzing public sentiment through machine learning techniques.

Several key findings emerged. First, the analysis of social media data presented a viable method for obtaining real-time information on disaster damage and the corresponding demand for relief supplies. In the case of Typhoon Yagi, shelter and transportation were identified as the most inadequate and dissatisfying areas, underscoring the need for improved preparedness by governmental and humanitarian entities. Second, the performance evaluation of machine learning models highlighted their effectiveness in enabling real-time and data-driven decision-making within post-disaster logistics. The integration of such analytical frameworks into disaster management systems allows authorities to dynamically assess community needs, optimize resource distribution, and enhance the responsiveness and agility of relief efforts through complementing, updating, and verifying information from official report channels.

From a policy and operational perspective, the findings suggested that government agencies and humanitarian organizations should incorporate social media sentiment analysis into their disaster response frameworks. Real-time monitoring of public sentiment can serve as an early-warning system for unmet needs and logistical gaps, enabling faster and more targeted interventions. Moreover, integrating sentiment data with traditional assessment tools, such as field surveys and satellite imagery, could provide a holistic view of disaster impacts. Governments should invest in developing digital infrastructure, data science capacity, and cross-platform data integration tools to ensure that such systems are scalable and reliable during crises. These could improve response efficiency and ensure that disaster relief efforts are more adaptive, inclusive, and attuned to the voices of affected communities.

While this study affirmed the feasibility and value of integrating social media sentiment analysis with machine learning for timely, data-informed, and community-centered disaster response, future research should expand the diversity of datasets to support deep learning models. For example, data can be collected from other platforms (e.g., Zalo, Otofun, Tinhte, and Voz) and multiple languages (Vietnamese, English, and languages of ethnic minorities in Vietnam). In addition, the focus of studies should be extended to encompass a broader spectrum of natural disasters beyond typhoons, thereby enhancing the accuracy, representativeness, and depth of humanitarian logistics assessments. Furthermore, in post-disaster phase, there may be quite a number of independent voluntary donors who will do charity works by themselves. Thus, future research should consider building an open digital platform to provide real-time information about victims and relief demands for updating governments, non-governmental organizations as well as voluntary donors.

Author Contributions

Conceptualization, H.T.T. and D.A.N.; methodology, H.T.T.; software, D.A.N.; validation, H.T.T. and D.A.N.; formal analysis, H.T.T.; investigation, H.T.T. and D.A.N.; resources, H.T.T.; data curation, D.A.N.; writing—original draft preparation, D.A.N.; writing—review and editing, H.T.T.; visualization, D.A.N.; supervision, H.T.T.; project administration, H.T.T. All authors have read and agreed to the published version of the manuscript.

Data Availability

Not applicable.

Conflicts of Interest

The authors declare no conflict of interest.

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