 https://doi.org/10.1051/itmconf/20246503016

Unveiling the Role of social media in Shaping Responses to Natural Disasters

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Abstract: Natural disasters pose significant challenges to affected communities, governments, and relief organizations, necessitating innovative disaster response and recovery strategies. The rise of social media platforms in recent years has transformed disaster management, presenting both opportunities and complexities. This study delves into the multifaceted role of social media in shaping natural disaster responses. Researchers examine its utilization before, during, and after disasters for information dissemination, relief coordination, resource mobilization, and emotional support. Additionally, employing classification models like Support Vector Machine (SVM), Logistic Regression (LR), and Decision Tree (DT), the study assesses their performance using accuracy, recall, precision, and F1 score metrics. The SVM model achieves 94% accuracy, with 92% precision and 94% recall, resulting in a 95% F1 score. LR demonstrates similar performance, scoring 95% across accuracy, precision, and recall, yielding a corresponding 95% F1 score. In contrast, the DT model outperforms both, achieving 97% accuracy, 96% precision, and recall, culminating in an impressive 97% F1 score. These results highlight nuances in model efficacy, with DT showcasing superior performance. Moreover, the DT model exhibits a faster computation time at 37.203 ms compared to SVM and LR. This research sheds light on the dynamic relationship between social media and disaster response, offering insights for stakeholders to harness its potential in bolstering preparedness, response, and resilience during natural disasters.

Keywords: Social Media, Natural Disaster, Disaster Management, Crisis, Communication

I. INTRODUCTION

Social media refers to a wide variety of online platforms as well as technology that enable user collaboration, content sharing, and social engagement [1][2]. These social media sites comprise, but are not restricted to, Instagram, Snapchat, LinkedIn, Facebook, and Twitter. Social media has revolutionized how individuals link together, share information, and interact with one another on a worldwide scale and has become an essential component of modern communication [3][4]. One cannot exaggerate the impact that social media has made on modern society, as it has changed communication, commerce, politics, and entertainment, among other facets of human existence [5][6]. Research on social media is crucial due to its pervasive influence and evolving nature [7][8]. Understanding the dynamics of social media usage, its effects on individuals and society, and its potential applications is essential for policymakers, businesses, researchers, and the general public alike [9][10].

As social media continues to shape public discourse, influence consumer behaviour, and impact social interactions, research becomes instrumental in informing strategies for harnessing its benefits while mitigating its potential drawbacks, such as misinformation, privacy concerns, and online harassment [11]. One area of research regarding social media is its role in natural disasters [12-14]. During crises such as earthquakes, hurricanes, wildfires, and floods, social media platforms serve as vital communication channels for affected communities, emergency responders, and relief organizations [15][16]. Users turn to platforms like Twitter and Facebook to seek and share real-time updates, offer assistance, coordinate rescue efforts, and disseminate critical information such as evacuation orders, shelter locations, and emergency contact numbers [17][18]. The decentralized nature of social media enables rapid information dissemination, bypassing traditional communication barriers and reaching a wide audience instantaneously [19][20].

Images posted on social media during natural disasters are extremely important for recording the amount of the devastation, emphasizing how urgent the situation is, and galvanizing support from the public for relief efforts [21][22]. Pictures and videos captured by eyewitnesses provide firsthand accounts of the disaster's impact, helping authorities assess the situation, allocate resources effectively, and prioritize response efforts [23][24]. Additionally, visual content humanizes the crisis, evoking empathy and solidarity among online communities, which could galvanize support and donations for affected individuals and communities [25]. Figure 1 shows how social media is used in disaster detection and management.

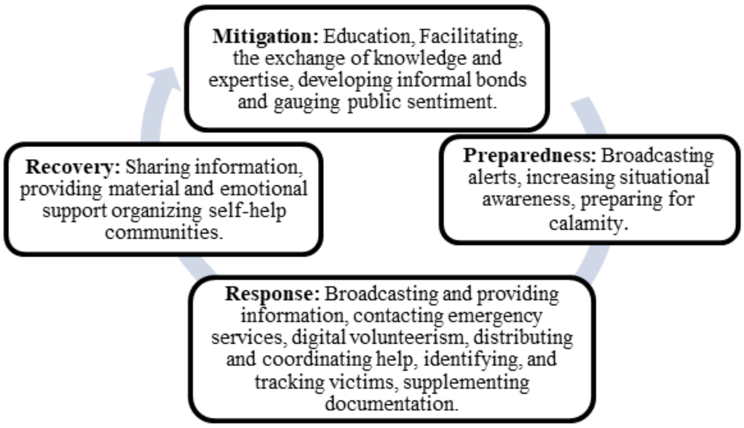

Figure 1: Use of social media in disaster management

There are various ways to leverage social media for effective disaster response and recovery efforts [27-29]. Initially, social media monitoring technologies might be employed by government agencies, emergency response teams, and humanitarian groups to monitor pertinent keywords, hashtags as well, and geotagged posts to detect new dangers, evaluate public opinion, and evaluate the efficacy of their communication tactics [30][31]. Secondly, these entities could establish official social media accounts to provide accurate and timely updates, address rumours and misinformation, and engage directly with the public to answer questions and provide assistance [32][33]. Moreover, community-based initiatives and grassroots organizations could harness the power of social media to mobilize volunteers, organize donation drives, and coordinate relief efforts at the local level [34]. By leveraging social networks, these initiatives could reach a broader audience, amplify their message, and rally support from individuals and businesses within the community. Additionally, social media platforms offer crowdfunding tools that enable individuals to raise funds for disaster relief efforts, providing a decentralized alternative to traditional fundraising methods [35].

The problems in exploring the role of social media in shaping responses to natural disasters lie in understanding how information dissemination, communication dynamics, and public engagement through platforms like Twitter, Facebook, and Instagram influence disaster preparedness, response strategies, and recovery efforts. Specifically, this research aims to investigate the effectiveness of social media in facilitating real-time information exchange, fostering community resilience, and coordinating humanitarian aid during crises while also addressing challenges such as misinformation propagation, digital divides, and privacy concerns. To overcome these challenges, this research aimed:

- To unveil the role of social media in shaping a response to natural disasters for early and better disaster recovery.
- To develop a web-based GUI system using Machine Learning (ML) and ensembled models.
- To enhance the overall prediction of the system for better and early detection of natural disasters.
- To evaluate the performance of the proposed disaster detection model, it is compared with the pre-developed model.

This research contributes to the interdisciplinary field of disaster management by exploring the transformative potential of social media, developing innovative technological solutions for disaster prediction and response, and rigorously evaluating the effectiveness of these solutions through empirical research and performance assessments. These contributions collectively aim to enhance societal resilience and mitigate the impact of natural disasters through informed decision-making and proactive interventions.

The remaining sections of this work are organized as follows. In Section 2, previous research is examined and addressed. Section 3 evaluates the proposed methodology and looks at the implications. The results are reviewed in Section 4, along with a short explanation for better understanding. Section 5 concludes the study and provides some reflections on possible future research directions.

II. REVIEW OF LITERATURE

In this section discussion about the previous work of various authors on Unveiling the Role of social media in Shaping Responses to Natural Disasters is mentioned. In 2021, Kim et al. [36] studied the unique ways in which Twitter in the US and China Weibo handle online riots. The investigation is conducted by doing a quantitative evaluation of the most popular trending phrases and related tweets over six months on social networking websites. The words that were trending in the US (United States) with Chinese platforms had considerably different targets, according to chi-square analysis. Before that, Li et al. (2020) [37] presented a new quantitative approach to studying community resilience during power outages, using the July 2019 blackout in Manhattan as a case study. The research used sentiment and behaviour analysis to look at the community. The mental as well as behavioral outcomes show that over an hour and a half following the blackout, New York City rebounded, suggesting a robust community's ability to withstand such brief and unexpected power outages.

Previously, Ferreira et al. (2020) [38] uncovered the means by which individuals obtained COVID-19-related material, their critical reactions to diverse sources, and their methods for evaluating the credibility of various media. According to the findings, there is a media dependency issue going on, with regular media being the primary source of information, and people have a high level of trust in conventional media. In 2020, Belso-Martinez et al. [39] determined that associations and knowledge agents play the most important roles. On the flip side, intermediary positions for coordinating or connecting separate activities of distinct organizations were uncommon among municipal and non-local administrations. Finally, for future response network collaboration, coordination, and performance, the results provide crucial advice for practitioners. Before this, Kersten et al. (2020) [40] provided a complex and elaborate picture of what happens in the impacted regions. In order to accomplish this, it was employed by adaptable and quick analysis techniques that provide supplementary and distinct perspectives on the data. Excelled among all entries in the TREC 2018 Incident Streams competition with F1 scores of approximately 0.55 for actionable classes (McCreadie, 2019).

Furthermore, Almaatouq et al. (2020) [41] investigated two pathways: 1) a global adaptation technique wherein the network's structural connectivity modifies itself to amplify the estimates of group members with high performance, and 2) a local modification mechanism wherein accurate individuals are less susceptible to social influence. Hence, when plasticity and feedback are present, social networks could adjust to biased and dynamic information environments, resulting in collective estimates that outperform their top-performing individual. Before this, Fatma Elzahraa Elsayed (2020) [42] eliminated the obstacles that hinder the operation of modern media technologies. The study issues are thoroughly investigated through the use of mixed methodology, which interweaves the questionnaire's qualitative results with those of the semi-structured interviews. In light of the Rohingya crisis, this research verified the assumptions about social information processing.

Previously, Shahsavari et al. (2020) [43] found a system that could be used to generate conspiracy theories and rumours through ML. Over time, the completeness score eventually reached about 92%, while the homogeneity score peaked at 82%, according to the results. Around 86% is the saturation point of the V-measure. These scores show the accuracy of the cluster-matching procedure for each time sample. In 2020, Li et al. [44] studied text data from China's biggest social media network during the COVID-19 outbreak to determine the impact of information richness and timeliness on public engagement. The author made use of text mining and NLP (natural language processing) based similarity computation method. According to the data, there was a negative correlation between information retrospectiveness and public involvement breadth and a positive correlation with depth. Before 2020, Frey and Ramirez (2019) [45] examined Red Riesgos's multi-tiered risk governance network's institutional relationships. It proved that local governments, playing a leading role, must be able to engage residents and communities, as well as maintain constant communication with higher-level authorities, for multi-level disaster-risk management networks to be effective. Previously, Spialek et al. (2019) [46] researched the correlation between PTS, PTG, and citizen disaster communication in North Carolina areas hit by Hurricane Matthew around six weeks after the storm. In order to improve public mental health response as well as coordination in the aftermath of a disaster, the results demonstrated the necessity of strong disaster communication ecosystems.

III. RESEARCH METHODOLOGY

In predicting natural disasters from social media posts, the process involves collecting the dataset, preprocessing the data to remove noise, extracting features using k-fold cross-validation, selecting features with Principal Component Analysis (PCA), dividing the dataset for training and testing, training models like SVM, LR, and DT, applying an ensemble model for classification, and ultimately predicting natural disasters. Lastly, the model's efficacy in precisely detecting content linked to disasters is assessed using metrics such as accuracy and score. This streamlined approach ensures a systematic and efficient method for leveraging social media data in disaster prediction and response.

A. Technique Used

This section details the technologies utilized in the methodology for feature selection, extraction, and model training, providing a comprehensive description of each technology's role and application within the research framework.

K-Fold: The K-fold cross validation is a technique that is utilized in social media content datasets for the purpose of evaluating the performance of predictive models and determining their generalizability. The process entails partitioning the data set into k subsets or folds of equal size. A total of k1 folds are used to train the model, and the remaining fold is used to validate it [47]. This procedure is carried out k times, with every fold acting to be the validation set precisely once in each instance. In order to achieve a reliable estimation of the model's performance, the performance measures from every iteration are then utilized to calculate an average. In the process of extracting features, the k-fold cross-validation technique could be utilized to assess the efficacy of various feature sets and to guarantee that the performance of the model is not unduly dependent on subsets of data [48].

PCA: Principal Component Analysis, also known as PCA, is a statistical method that is utilized for the purpose of reducing the dimensionality of datasets [49]. PCA is used to identify the prominent features in the prediction of natural disasters via social media datasets. The feature prediction is accomplished by reducing the initial variables to a smaller set of principal components, which are variables that are linearly uncorrelated with one another. The maximum amount of variation that exists within the data is captured by these components. PCA could successfully reduce the dimensions of the data set while maintaining its vital information. The dimensionality reduction is accomplished by retaining elements that describe most of the variance in the dataset [50]. This simplified dataset makes it possible to do modelling that is both more efficient and precise, which helps in the detection of natural disasters as well as other problems.

SVM: SVM stands for support vector machine, and it is a technique for ML that is utilized for regression and classification applications. The regression and classification allow the model to understand patterns and links between numerous natural disaster characteristics and the social media posts that are produced as a result [51]. By defining a hyperplane that best separates different classes of data points, SVM maximizes the margin between classes, aiming to achieve optimal generalization performance. Through training, SVM identifies the most discriminative features and constructs a predictive model capable of accurately estimating the intensity of natural disasters based on input variables such as Instagram posts, Twitter (tweets), and damage management practices [52]. In Figure 2, a visualization of the SVM is provided.

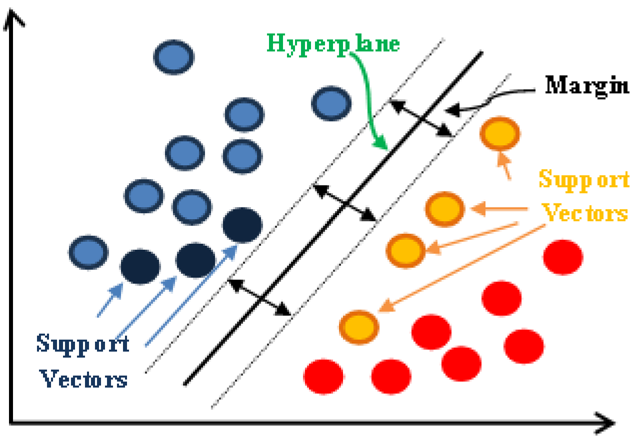

Figure 2: SVM visualization [53]

LR: LR stands for Logistic Regression, a statistical method used for binary classification tasks. In the context of training models for the detection of natural disasters, LR is employed to model the relationship between input features and the likelihood of a specific outcome [54]. By fitting a logistic function to the data, LR estimates the probability of a particular outcome occurring. During training, the LR model learns the weights of input features to best predict the intensity of the disaster. LR is valuable for its simplicity, interpretability, and effectiveness in modelling relationships between variables in disaster detection models. Figure 3 represents the diagrammatic view of LR.

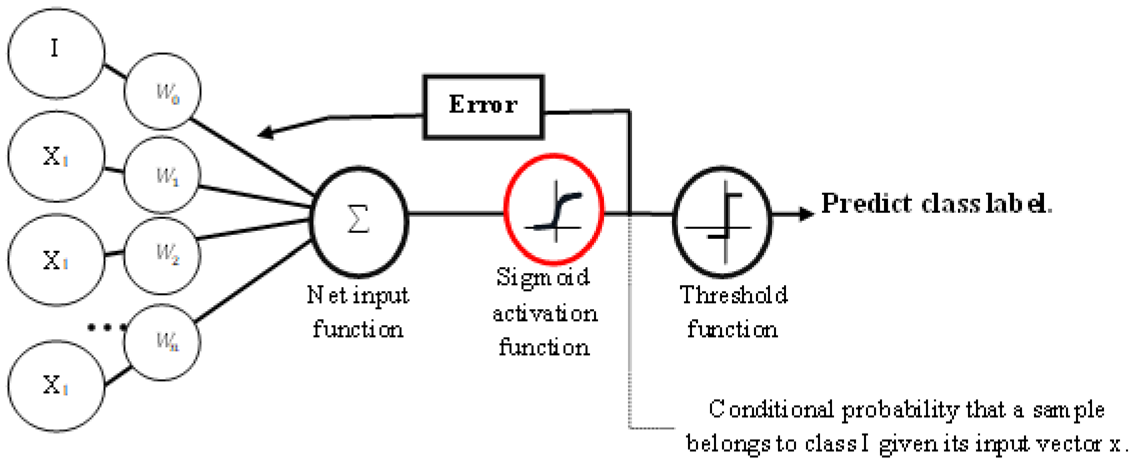

Figure 3: LR diagrammatic representation [55]

DT: DT stands for Decision Trees, a popular ML algorithm. In training, DTs analyze historical data on social media alongside various factors like tweets on Twitter, Instagram posts, and other platforms having social communities. It builds a treelike structure where each internal node represents a decision based on input features, and each leaf node corresponds to a predicted intensity of disaster [56]. The algorithm learns to make these decisions by recursively partitioning the data into subsets, aiming to minimize impurity or maximize information gain at each step. Ultimately, DTs offer a transparent and interpretable model for understanding the factors influencing social media towards natural disasters. Figure 4 represents the structure of a DT.

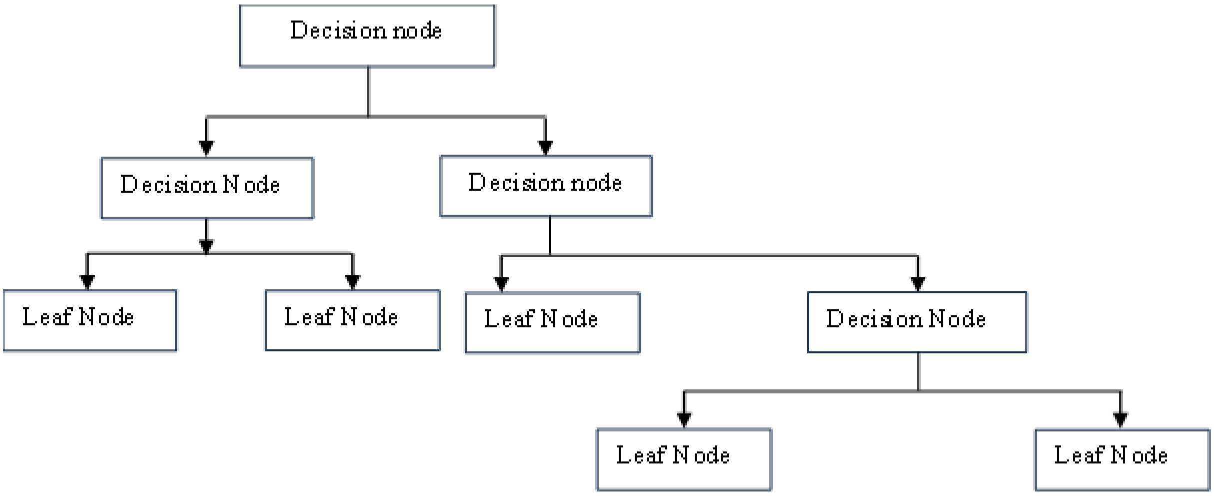

Figure 4: DT Diagrammatic Representation [57]

B. Proposed Architecture

This section includes information about the architecture used to design natural disaster prediction via social media. Figure 5 shows the architecture of the proposed mechanism.

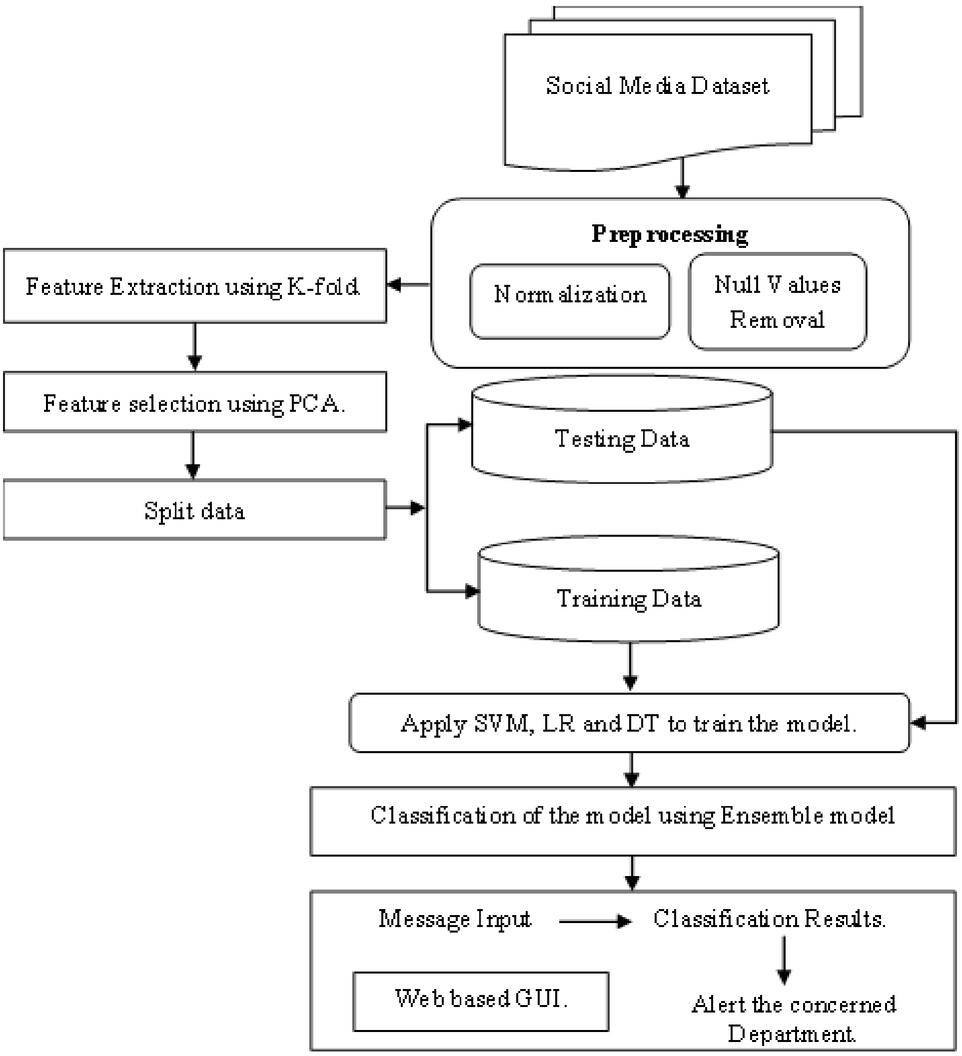

Figure 5: Architecture of Proposed Methodology

C. Proposed Algorithm

This section describes the model used to gain the best result for natural disaster detection using social media content via the following steps.

Step 1. Selection of Dataset:

A dataset containing social media posts related to natural disasters, including features such as text content, timestamps, and user metadata. Let D be the dataset containing n and m features.

Step 2. Preprocessing of Data:

- Normalization of the dataset: Normalize the timestamps and other numerical function f.
- For each function f in D

$$\text{Normalization\_value (f)} = \frac{\text{Value(f)} - \text{Mean(f)}}{\text{Standard\_daviation(f)}} \quad (1)$$

Removal of null values: Drop the rows containing null values.

Step 3. Feature Extraction using K-fold:

- Split the dataset D into K folds.
- For iin range k:
- Use k-1 folds for training and the remaining fold for validation.

Step 4. Feature Selection using PCA:

Apply PCA to reduce the dimensionality of the dataset while preserving valuable information. PCA involves the eigen decomposition of the covariance matrix of the dataset D.

$$\text{Convariance matrix} = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})(x_i - \bar{x})^T \quad (2)$$

Where x_i is a sample in D and $\bar{x}$ is the mean of D.

Compute the eigenvectors and eigenvalues of the covariance matrix.

Select the top k eigenvectors corresponding to the largest eigenvalues as principal components.

Step 5. Dividing the Dataset into Training and Testing:

It involves splitting the dataset into training (D_training) and testing (D_testing) sets, typically using a certain ratio.

Step 6. Training of the Model:

Training involves optimizing the parameters of each model. For example, in SVM, LR, and DT:

•SVM: SVM aims to find the optimal hyperplane that separates different classes in the feature space.

$$min_{w,b}\frac{1}{2}||\mathrm{w}||^2 \quad (3)$$

Subject to

$$y_i\big((w * x_i) + b\big) \geq 1 = 1, \dots., n. \quad (4)$$

LR: LR is a probabilistic model that estimates the probability of a sample belonging to a particular class.

$$max_\beta \sum_{i-1}^{n}(y_i * (\beta * x) - \log(1 + e^{\beta * x_i})) \quad (5)$$

DT: It involves recursively partitioning the feature space based on impurity measures like Gini impurity or entropy.

Step 7. Classification of the Model using Ensemble Model:

For the ensemble model, if using a simple majority voting classifier.

$$\hat{y} = argmax_y \sum_{i-1}^{N} 1(y_i = y) \quad (6)$$

where $\hat{y}$ Iis the predicted class label, N is the number of base models, and 1 is the indicator function

Step 8. Output through Web-Based GUI based on Input Message:

- Develop a web-based GUI that takes an input message.
- Preprocess the input message similar to step 2.
- Extract features using PCA.
- Use the ensemble model to classify the input message into appropriate categories.

IV. RESULT AND DISCUSSION

The following section describes the dataset used in this research. Additionally, this section provides an analysis of the results obtained from the conducted experiments.

A. Dataset Description

Twitter, a popular microblog with 135 million active users who post more than 400 million tweets daily, was selected as the secondary sentiment analysis object for this study due to its social media nature. A total of 42,897 valid tweets were collected for these natural catastrophes. Twitter Scraper was employed to gather Twitter content for this study. Combinations of natural disasters and necessities are the keywords that are used to gather this information. Every natural disaster has a one-week lead time before and after it, and this lead time was followed when gathering the data. Table 1 contains the following list of examples of keywords and periods that were utilized to collect data.

TABLE 1
DATA COLLECTION

Disaster	**Keyword**	**Time Frame**
Tornado	tornado + housing/transportation/food/medical supplies	04/18/2021 - 05/05/2021
Hurricane Harvey	Hurricane Harvey + housing/transportation/food/medical 08/10/2017 - 09/09/2017 Supplies	08/10/2020 - 09/09/2020
Floods	floods + housing/transportation/food/medical supplies	09/02/2022 - 01/07/2023
Wildfires	Wildfires+ housing/transportation/food/medical supplies	07/31/2022 - 11/15/2022

B. Evaluation Metrics

The accuracy, precision, recall, and F1-score are the four metrics used to measure the performance of the classification techniques. The following are the relevant metric formulas:

- Accuracy: Accuracy is defined as the ratio of the number of cases that yielded correct results to the total number of cases that were searched.

  $$\text{Accuracy: } \frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{7}$$

- Precision: Precision measures the proportion of true positive results among the total predicted positives. Precision measures the accuracy of positive predictions.

  $$\text{Precision} = \frac{\text{TP}}{\text{TP+FP}} \tag{8}$$

- Recall (Sensitivity): Recall measures the proportion of true positive results among the actual positives. Recall measures the proportion of actual positives that were correctly identified.

  $$Recall = \frac{TP}{TP+FN} \tag{9}$$

- F1 Score: The F1 score is the harmonic mean of precision and recall. It provides a balance between precision and recall.

  $$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{10}$$

Where True Positives (TP), False Positives (FP), True Negatives (TN), False Negatives (FN).

To avoid confusion, the family name must be written as the last part of each author name.

Each affiliation must include, at the very least, the name of the company and the name of the country wherethe author is based.

C. Performance Evaluation

The collection of data provides an overview of the classification of the social media dataset on Twitter using several ML models. In terms of average prediction accuracy, the authors rank the DT model first with the SVM and Logistics Regression model. Complex tasks, such as processing images and sounds, are better handled by ML models. Accuracy, defined as the percentage of samples with valid predictions relative to the total observations, is often considered the most intuitive performance metric. But accuracy isn't a telltale sign of an ML model's qualities particularly in unbalanced datasets.

Table 2 shows the accuracy of three different ML models, SVM, LR, and DT, in predicting four different natural disasters (tornadoes, hurricanes, floods, and wildfires). The SVM model achieved an accuracy of 0.93 for predicting tornadoes, 0.97 for predicting Hurricane Harvey, 0.93 for predicting floods, 0.93 for predicting wildfires, meaning it correctly predicted tornadoes 93%, hurricane Harvey 97%, floods 93%, wildfires 93%of the time. The LR model achieved an accuracy of 0.96 for predicting tornadoes, 0.95 for predicting Hurricane Harvey, 0.95 for predicting floods, and 0.97 for predicting wildfires, meaning it correctly predicted tornadoes 96%, hurricane Harvey 95%, floods 95%, wildfires 97% of the time. The DT model achieved an accuracy of 0.95 for predicting tornadoes, 0.98 for predicting Hurricane Harvey, 0.98 for predicting floods, and 0.97 for predicting wildfires, meaning it correctly predicted tornadoes 95%, hurricane Harvey 98%, floods 98%, wildfires 97% of the time.

TABLE 2
ACCURACIES FOR THE CLASSIFICATION

Model	Tornado	Hurricane Harvey	Floods	Wildfires	Average Accuracy
SVM	0.93	0.97	0.93	0.93	0.94
LR	0.96	0.95	0.95	0.97	0.95
DT	0.95	0.98	0.98	0.97	0.97

Figure 6 compares the accuracy of four different forecasting models for tornadoes, hurricanes, floods, and wildfires. The four models are SVM, LR, and DT. The x-axis of the graph shows the types of natural disasters, while the y-axis shows the accuracy of the models in forecasting them.

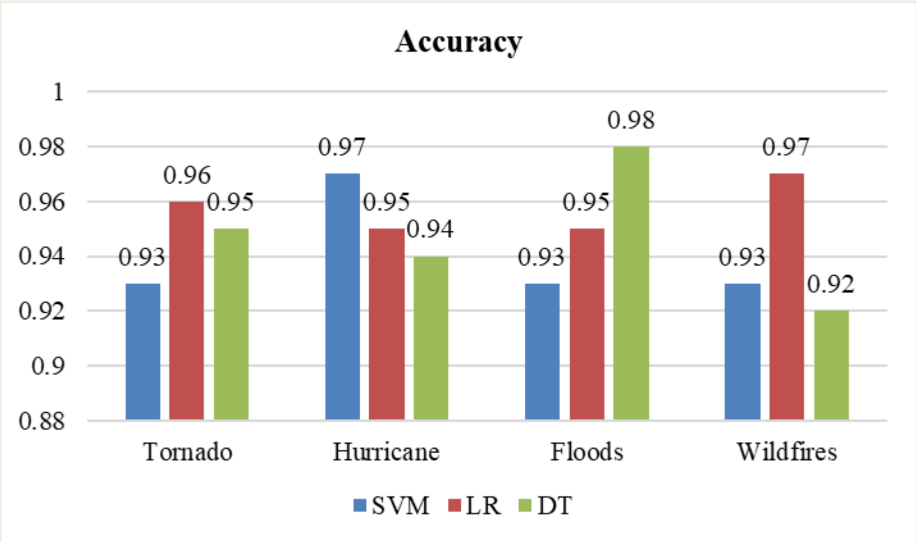

Figure 6: Classification of Accuracy

Table 3 shows the precision of three different ML models, SVM, LR, and DT, predicting four different natural disasters (tornadoes, hurricanes, floods, and wildfires). The SVM model achieved a precision of 0.90 for predicting tornadoes, 0.91 for predicting Hurricane Harvey, 0.93 for predicting floods, 0.97 for predicting wildfires, meaning it correctly predicted tornadoes 90%, hurricane Harvey 91%, floods 93%, wildfires 97% of the time. The LR model achieved a precision of 0.91 for predicting tornadoes, 0.99 for predicting Hurricane Harvey, 0.94 for predicting floods, and 0.96 for predicting wildfires, meaning it correctly predicted tornadoes 91%, hurricane Harvey 99%, floods 94%, wildfires 96% of the time. The DT model achieved a precision of 0.98 for predicting tornadoes, 0.95 for predicting Hurricane Harvey, 0.96 for predicting floods, and 0.96 for predicting wildfires, meaning it correctly predicted tornadoes 98%, hurricane Harvey 95%, floods 96%, wildfires 96% of the time.

TABLE 3
PRECISION FOR THE CLASSIFICATION

Model	**Tornado**	**Hurricane Harvey**	**Floods**	**Wildfires**	**Average Precision**
SVM	0.90	0.91	0.93	0.97	0.92
LR	0.91	0.99	0.94	0.96	0.95
DT	0.98	0.95	0.96	0.96	0.96

Figure 7 compares the precision of four different forecasting models for tornadoes, hurricanes, floods, and wildfires. The four models are SVM, LR, and DT. The x-axis of the graph shows the types of natural disasters, while the y-axis shows the accuracy of the models in forecasting them.

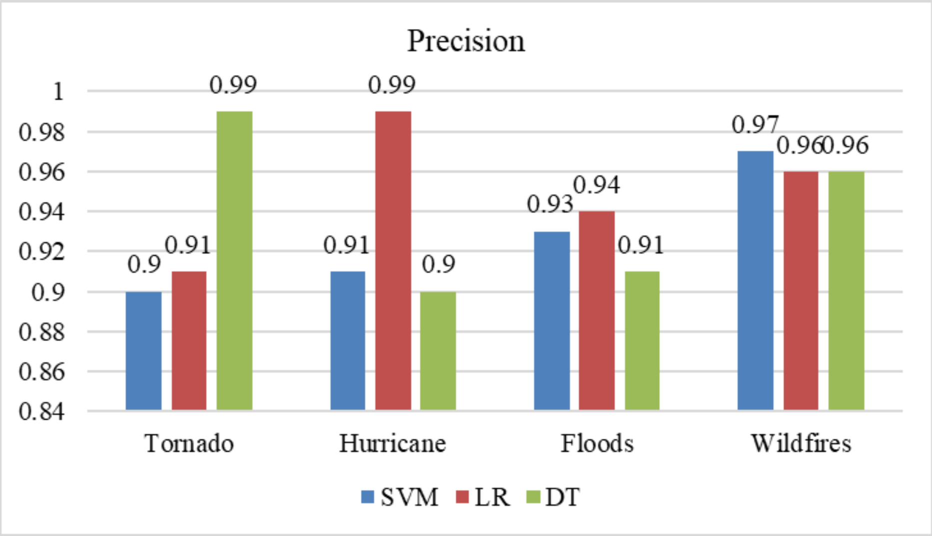

Figure 7: Classification of Precision

Table 4 shows the recall of three different ML models, SVM, LR, and DT, predicting four different natural disasters (tornadoes, hurricanes, floods, and wildfires). The SVM model achieved a recall of 0.96 for predicting tornadoes, 0.91 for predicting Hurricane Harvey, 0.98 for predicting floods, 0.94 for predicting wildfires, meaning it correctly predicted tornadoes 96%, hurricane Harvey 91%, floods 98%, wildfires 94% of the time. The LR model achieved a recall of 0.92 for predicting tornadoes, 0.97 for predicting Hurricane Harvey, 0.95 for predicting floods, 0.93 for predicting wildfires, meaning it correctly predicted tornadoes 92%, hurricane Harvey 97%, floods 95%, wildfires 93% of the time. The DT model achieved a recall of 0.98 for predicting tornadoes, 0.97 for predicting Hurricane Harvey, 0.95 for predicting floods, and 0.97 for predicting wildfires, meaning it correctly predicted tornadoes 98%, hurricane Harvey 97%, floods 95%, wildfires 97% of the time.

TABLE 4
RECALL FOR THE CLASSIFICATION

Model	**Tornado**	**Hurricane Harvey**	**Floods**	**Wildfires**	**Average Recall**
SVM	0.96	0.91	0.98	0.94	0.94
LR	0.92	0.97	0.95	0.93	0.94
DT	0.98	0.97	0.95	0.97	0.96

Figure 8 compares the recall of four different forecasting models for tornadoes, hurricanes, floods, and wildfires. The four models are SVM, LR, and DT. The x-axis of the graph shows the types of natural disasters, while the y-axis shows the accuracy of the models in forecasting them.

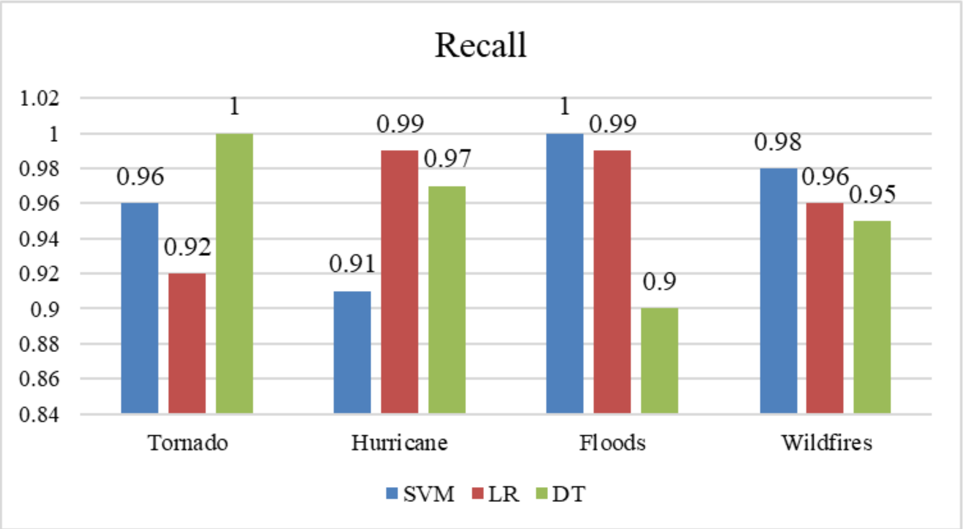

Figure 8: Classification of Recall

Table 5 shows the f1-score of three different ML models, SVM, LR, and DT, predicting four different natural disasters (tornadoes, hurricanes, floods, and wildfires). The SVM model achieved an f1-score of 0.93 for predicting tornadoes, 0.96 for predicting Hurricane Harvey, 0.96 for predicting floods, 0.97 for predicting wildfires, meaning it correctly predicted tornadoes 93%, hurricane Harvey 96%, floods 96%, wildfires 97% of the time. The LR model achieved a score of 0.94 for predicting tornadoes, 0.98 for predicting Hurricane Harvey, 0.95 for predicting floods, 0.96 for predicting wildfires, meaning it correctly predicted tornadoes 94%, hurricane Harvey 98%, floods 95%, wildfires 96% of the time. The DT model achieved an f1-score of 0.97 for predicting tornadoes, 0.98 for predicting Hurricane Harvey, 0.96 for predicting floods, 0.97 for predicting wildfires, meaning it correctly predicted tornadoes 97%, hurricane Harvey 98%, floods 96%, wildfires 97% of the time.

TABLE 5
F1-SCORE FOR THE CLASSIFICATION

Model	Tornado	Hurricane Harvey	Floods	Wildfires	Average F1-score
SVM	0.93	0.96	0.96	0.97	0.95
LR	0.94	0.98	0.95	0.96	0.95
DT	0.97	0.98	0.96	0.97	0.97

Figure 9 compares the f1-score of four different forecasting models for tornadoes, hurricanes, floods, and wildfires. The four models are SVM, LR, and DT. The x-axis of the graph shows the types of natural disasters, while the y-axis shows the accuracy of the models in forecasting them.

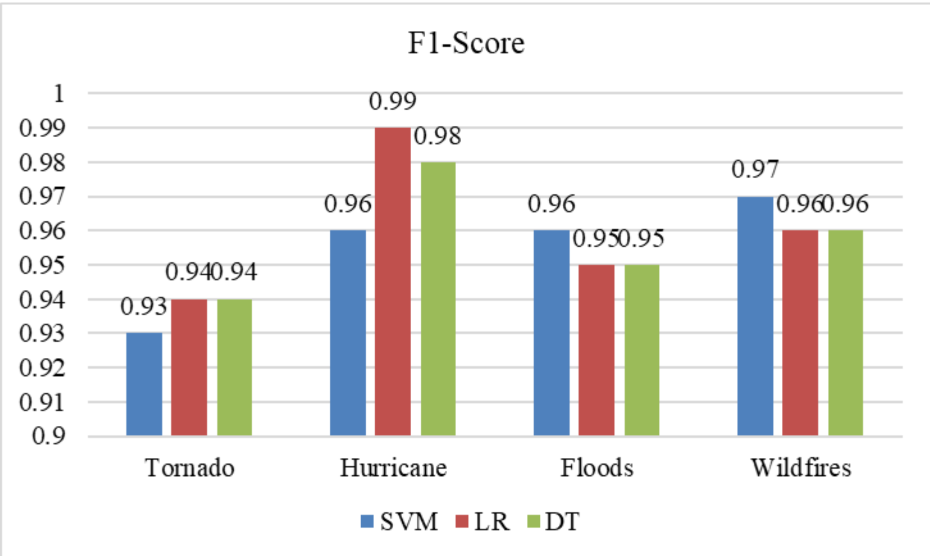

Figure 9: Classification of F1-Score

V. COMPARATIVE ANALYSIS

Table 6 demonstrates the computation table of computation time and accuracy for ML models. Table shows the average computation time for three different ML models. The models are SVM, LR, and DT. DT has the fastest average computation time, 37.20 seconds. LR has a computation time of 812.16 seconds, which is more than 21 times slower than DT. SVM is the slowest model, with an average computation time of 1250.20 seconds, which is more than 33 times slower than DT.

TABLE 6
COMPUTATION TABLE FOR ML MODELS

Model	Computation Time
Support Vector Machine	1250.20
Logistic Regression	812.16
Decision Tree	37.20

Figure 10 depicts the performance of three ML models, namely SVM, LR, and DT. It compares two aspects of their performance: accuracy and computation time. On the x-axis is computation time, likely measured in milliseconds (ms). The y-axis represents accuracy measured in percentage. The SVM model appears with an accuracy of around 94% but also has the longest computation time, around 1250.20 ms. LR model with an accuracy of around 95%, with a computation time of around 812.16 ms. DT appears to be the more accurate model, around 97% accuracy, but also has the shortest computation time, around 37.20 ms. DT provides the most accurate results, but they take the minimum time to compute. SVM, on the other hand, is the slowest to compute and has the least accuracy.

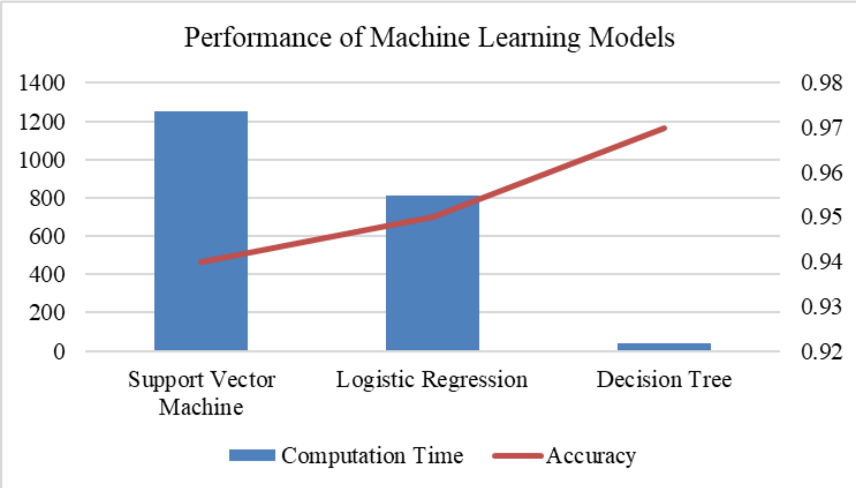

Figure 10: Comparison of Computational Time

VI. CONCLUSION AND FUTURE SCOPE

The profound influence of social media on responses to natural disasters is evident in its diverse impact on information dissemination, community mobilization, and disaster relief coordination. This research provides valuable insights into its pivotal role. The results show that the SVM model achieves 94% accuracy, with precision and recall at 92% and 94%, respectively, resulting in a 95% F1 score. LR performs similarly, boasting 95% accuracy, precision, and recall, leading to a corresponding 95% F1 score. In comparison, the DT model outperforms both, achieving 97% accuracy, 96% precision, and recall, culminating in a remarkable 97% F1 score. These findings reveal nuances in model efficacy, with DT exhibiting superior accuracy, precision, and recall. Moreover, the DT model demonstrates a faster computation time at 37.203 ms compared to SVM and LR. Future research avenues include exploring ensemble methods, deeper sentiment analysis, and real-time data integration. Collaboration between researchers, social media platforms, and disaster management agencies is vital to tailor solutions effectively.

ACKNOWLEDGMENT

The heading of the Acknowledgment section and the References section must not be numbered. Causal Productions wishes to acknowledge Michael Shell and other contributors for developing and maintaining the IEEE LaTeX style files which have been used in the preparation of this template.

REFERENCES

[1] Aichner, Thomas, Matthias Grünfelder, Oswin Maurer, and Deni Jegeni. "Twenty-five years of social media: a review of social media applications and definitions from 1994 to 2019." Cyberpsychology, behaviour, and social networking 24, no. 4 (2021): 215-222.
[2] Kapoor, Kawaljeet Kaur, Kuttimani Tamilmani, Nripendra P. Rana, Pushp Patil, Yogesh K. Dwivedi, and Sridhar Nerur. "Advances in social media research: Past, present and future." Information Systems Frontiers 20 (2018): 531-558.
[3] Bossetta, Michael. "The digital architectures of social media: Comparing political campaigning on Facebook, Twitter, Instagram, and Snapchat in the 2016 US election." Journalism & Mass Communication Quarterly 95, no. 2 (2018): 471-496.
[4] Ahuja, Yukti, and Kashika Chadha. "Content Sharing and Communication on Social Media Platforms: A Review." IUP Journal of Management Research 21, no. 1 (2022).
[5] Flew, Terry, and Petros Iosifidis. "Populism, globalisation and social media." International Communication Gazette 82, no. 1 (2020): 7-25.
[6] Chadwick, Andrew. "The new crisis of public communication: Challenges and opportunities for future research on digital media and politics." (2019).
[7] Peng, Sancheng, Yongmei Zhou, Lihong Cao, Shui Yu, Jianwei Niu, and Weijia Jia. "Influence analysis in social networks: A survey." Journal of Network and Computer Applications 106 (2018): 17-32.
[8] Peng, Sancheng, Yongmei Zhou, Lihong Cao, Shui Yu, Jianwei Niu, and Weijia Jia. "Influence analysis in social networks: A survey." Journal of Network and Computer Applications 106 (2018): 17-32.
[9] Kapoor, Kawaljeet Kaur, Kuttimani Tamilmani, Nripendra P. Rana, Pushp Patil, Yogesh K. Dwivedi, and Sridhar Nerur. "Advances in social media research: Past, present and future." Information Systems Frontiers 20 (2018): 531-558.
[10] Enli, Gunn, and Chris-Adrian Simonsen. "'Social media logic ' meets professional norms: Twitter hashtags usage by journalists and politicians." Information, Communication & Society 21, no. 8 (2018): 1081-1096.
[11] Arijeniwa, Adedeji F., and Emeke Precious Nwaoboli. "Setting agenda for public discourse: Examining the impact of social media on political participation amongst Nigerian youth." International Journal of Arts, Humanities and Management Studies 10, no. 1 (2023): 36-53.
[12] Wang, Zheye, and Xinyue Ye. "Social media analytics for natural disaster management." International Journal of Geographical Information Science 32, no. 1 (2018): 49-72.
[13] Zhang, Cheng, Chao Fan, Wenlin Yao, Xia Hu, and Ali Mostafavi. "Social media for intelligent public information and warning in disasters: An interdisciplinary review." International Journal of Information Management 49 (2019): 190-207.

[14] Lovari, Alessandro, and Shannon A. Bowen. "Social media in disaster communication: A case study of strategies, barriers, and ethical implications." Journal of Public Affairs 20, no. 1 (2020): e1967.
[15] Shittu, Ekundayo, Geoffrey Parker, and Nancy Mock. "Improving communication resilience for effective disaster relief operations." Environment Systems and Decisions 38 (2018): 379-397.
[16] Kanellopoulos, Vasilis, Vassilis Trianatafyllou, Constantinos Koutsojannis, and Efthymis Lekkas. "The Role of Social Media to the Natural Disaster or Crisis Management." (2023).
[17] Young, Camila E., Camila E. Young, Erica D. Kuligowski, and Aashna Pradhan. A review of social media use during disaster response and recovery phases. US Department of Commerce, National Institute of Standards and Technology, 2020.
[18] Jahanian, Mohammad, Yuxuan Xing, Jiachen Chen, K. K. Ramakrishnan, Hulya Seferoglu, and Murat Yuksel. "The evolving nature of disaster management in the internet and social media era." In 2018 IEEE International Symposium on Local and Metropolitan Area Networks (LANMAN), pp. 79-84. IEEE, 2018.
[19] Dhall, Sakshi, Ashutosh Dhar Dwivedi, Saibal K. Pal, and Gautam Srivastava. "Blockchain-based framework for reducing fake or vicious news spread on social media/messaging platforms." Transactions on Asian and Low-Resource Language Information Processing 21, no. 1 (2021): 1-33.
[20] Te, Chanvathana. "Incorporating Social Media Technologies as Crisis Communication in the Digital Age: A Look At the Public Sector Lens." PhD diss., University of Massachusetts, 2021.
[21] Ogie, Robert I., Sharon James, A. Moore, Tasmin Dilworth, Mehrdad Amirghasemi, and Jushua Whittaker. "Social media use in disaster recovery: A systematic literature review." International Journal of Disaster Risk Reduction 70 (2022): 102783.
[22] Yu, Manzhu, Chaowei Yang, and Yun Li. "Big data in natural disaster management: a review." Geosciences 8, no. 5 (2018): 165.
[23] Zahra, Kiran, Muhammad Imran, and Frank O. Ostermann. "Automatic identification of eyewitness messages on Twitter during disasters." Information processing & management 57, no. 1 (2020): 102107.
[24] Imran, Muhammad, Ferda Ofli, Doina Caragea, and Antonio Torralba. "Using AI and social media multimodal content for disaster response and management: Opportunities, challenges, and future directions." Information Processing & Management 57, no. 5 (2020): 102261.
[25] Jambrešić Kirin, Renata, Katherine Borland, Stef Jansen, Jelena Marković, and Sanja Lončar. "To Touch, to Hear, to Feel. Could Ethnography Dissolve the Narrations of Fear?." Etnološka tribina: Godišnjak Hrvatskog etnološkog društva 52, no. 45 (2022): 3-80.
[26] Domalewska, Dorota. "The role of social media in emergency management during the 2019 flood in Poland." Security and Defence Quarterly 27, no. 5 (2019): 32-43.
[27] Joseph, Joice K., Karunakaran Akhil Dev, A. P. Pradeepkumar, and Mahesh Mohan. "Big data analytics and social media in disaster management." In Integrating disaster science and management, pp. 287-294. Elsevier, 2018.
[28] Jamali, Mehdi, Ali Nejat, Souparno Ghosh, Fang Jin, and Guofeng Cao. "Social media data and post-disaster recovery." International Journal of Information Management 44 (2019): 25-37.
[29] Saroj, Anita, and Sukomal Pal. "Use of social media in crisis management: A survey." International Journal of Disaster Risk Reduction 48 (2020): 101584.
[30] Khatoon, Shaheen, Majed A. Alshamari, Amna Asif, Md Maruf Hasan, Sherif Abdou, Khaled Mostafa Elsayed, and Mohsen Rashwan. "Development of social media analytics system for emergency event detection and crisis management." Comput. Mater. Contin 68, no. 3 (2021).
[31] Gulesan, Oya Benlioglu, Emrah Anil, and Pinar Sarisaray Boluk. "Social media-based emergency management to detect earthquakes and organize civilian volunteers." International Journal of Disaster Risk Reduction 65 (2021): 102543.
[32] Mitcham, Dionne, Morgan Taylor, and Curtis Harris. "Utilizing social media for information dispersal during local disasters: The communication hub framework for local emergency management." International Journal of Environmental Research and Public Health 18, no. 20 (2021): 10784.
[33] Kim, Jooho, and Makarand Hastak. "Social network analysis: Characteristics of online social networks after a disaster." International Journal of Information Management 38, no. 1 (2018): 86-96.
[34] Tye, Michelle, Carmen Leong, Felix Tan, Barney Tan, and Ying Hooi Khoo. "Social media for empowerment in social movements: the case of Malaysia's grassroots activism." Communications of the Association for Information Systems 42, no. 1 (2018): 15.
[35] Sirisawat, Siriphong, Pattanaporn Chatjuthamard, Supaporn Kiattisin, and Sirimon Treepongkaruna. "The future of digital donation crowdfunding." PLoS One 17, no. 11 (2022): e0275898.
[36] Kim, Sora, Kang Hoon Sung, Yingru Ji, Chen Xing, and Jiayu Gina Qu. "Online firestorms in social media: Comparative research between China Weibo and USA Twitter." Public Relations Review 47, no. 1 (2021): 102010.
[37] Li, Lingyao, Zihui Ma, and Tao Cao. "Leveraging social media data to study the community resilience of New York City to 2019 power outage." International Journal of Disaster Risk Reduction 51 (2020): 101776.
[38] Ferreira, Gil Baptista, and Susana Borges. "Media and misinformation in times of COVID-19: How people informed themselves in the days following the Portuguese declaration of the state of emergency." Journalism and Media 1, no. 1 (2020): 108-121.
[39] Belso-Martínez, Jose Antonio, Alicia Mas-Tur, Mariola Sánchez, and Maria Jose Lopez-Sanchez. "The COVID-19 response system and collective social service provision. Strategic network dimensions and proximity considerations." Service Business 14 (2020): 387-411.
[40] Kersten, Jens, and Friederike Klan. "What happens during disasters? A Workflow for the multifaceted characterization of crisis events based on Twitter data." Journal of Contingencies and Crisis Management 28, no. 3 (2020): 262-280.
[41] Almaatouq, Abdullah, Alejandro Noriega-Campero, Abdulrahman Alotaibi, P. M. Krafft, Mehdi Moussaid, and Alex Pentland. "Adaptive social networks promote the wisdom of crowds." Proceedings of the National Academy of Sciences 117, no. 21 (2020): 11379-11386.
[42] Elsayed, Fatma Elzahraa. "Social media role in relieving the Rohingya humanitarian crisis." New Media and Mass Communication 87, no. 1 (2020): 28-48.
[43] Shahsavari, Shadi, Pavan Holur, and Tianyi Wang. "Conspiracy in the time of corona: automatic detection of emerging." Journal of Computational Social Science, 3 (2) (2020).
[44] Li, Kai, Cheng Zhou, Xin Robert Luo, Jose Benitez, and Qinyu Liao. "Impact of information timeliness and richness on public engagement on social media during COVID-19 pandemic: An empirical investigation based on NLP and machine learning." Decision Support Systems 162 (2022): 113752.
[45] Frey, Klaus, and Daniel Ricardo Calderón Ramírez. "Multi-level network governance of disaster risks: the case of the Metropolitan Region of the Aburra Valley (Medellin, Colombia)." Journal of Environmental Planning and Management 62, no. 3 (2019): 424-445.
[46] Spialek, Matthew L., J. Brian Houston, and Kyle C. Worley. "Disaster communication, posttraumatic stress, and posttraumatic growth following Hurricane Matthew." Journal of Health Communication 24, no. 1 (2019): 65-74.
[47] Devaraj, Ashwin, Dhiraj Murthy, and Aman Dontula. "Machine-learning methods for identifying social media-based requests for urgent help during hurricanes." International Journal of Disaster Risk Reduction 51 (2020): 101757.
[48] Powers, Courtney J., Ashwin Devaraj, Kaab Ashqeen, Aman Dontula, Amit Joshi, Jayanth Shenoy, and Dhiraj Murthy. "Using artificial intelligence to identify emergency messages on social media during a natural disaster: A deep learning approach." International Journal of Information Management Data Insights 3, no. 1 (2023): 100164.
[49] Sit, Muhammed Ali, Caglar Koylu, and Ibrahim Demir. "Identifying disaster-related tweets and their semantic, spatial and temporal context using deep learning, natural language processing and spatial analysis: a case study of Hurricane Irma." In Social Sensing and Big Data

Computing for Disaster Management, pp. 8-32. Routledge, 2020.
[50] Pouyanfar, Samira, Yudong Tao, Haiman Tian, Shu-Ching Chen, and Mei-Ling Shyu. "Multimodal deep learning based on multiple correspondence analysis for disaster management." World Wide Web 22 (2019): 1893-1911.
[51] Alam, Firoj, Ferda Ofli, and Muhammad Imran. "Descriptive and visual summaries of disaster events using artificial intelligence techniques: case studies of Hurricanes Harvey, Irma, and Maria." Behaviour & Information Technology 39, no. 3 (2020): 288-318.
[52] Ragini, J. Rexiline, PM Rubesh Anand, and Vidhyacharan Bhaskar. "Mining crisis information: A strategic approach for detection of people at risk through social media analysis." International journal of disaster risk reduction 27 (2018): 556-566.
[53] Manjrekar, Onkar N., and Milorad P. Dudukovic. "Identification of flow regime in a bubble column reactor with a combination of optical probe data and machine learning technique." Chemical Engineering Science: X 2 (2019): 100023.
[54] Hao, Haiyan, and Yan Wang. "Leveraging multimodal social media data for rapid disaster damage assessment." International Journal of Disaster Risk Reduction 51 (2020): 101760.
[55] Torres, Renato, Orlando Ohashi, and Gustavo Pessin. "A machine learning approach to distinguish passengers and drivers reading while driving." Sensors 19, no. 14 (2019): 3174.
[56] Hao, Haiyan, and Yan Wang. "Leveraging multimodal social media data for rapid disaster damage assessment." International Journal of Disaster Risk Reduction 51 (2020): 101760.
[57] Torres, Renato, Orlando Ohashi, and Gustavo Pessin. "A machine learning approach to distinguish passengers and drivers reading while driving." Sensors 19, no. 14 (2019): 3174.