Impact of Social Media During Natural Calamity

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Abstract: This paper proposes a disaster management system based on machine learning, incorporating a web-based graphical user interface. The system involves six steps, starting with the inclusion of any disaster-related information into the message dataset. Two commonly used machine learning algorithms, random forest and logistic regression, are employed to evaluate the performance of the interface, achieving an accuracy of 72% and 73%, respectively, in classification and prediction tasks. The interface enables users to input messages containing relevant keywords classified based on predefined criteria. Afterward, the system automatically selects the relevant department for the particular disaster. The proposed system can enhance disaster management by simplifying the identification and response to disasters.

Keywords: social media, natural calamity, machine learning, disaster management, graphical user interface.

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1. Introduction

Communication and information exchange among users of social media platforms are becoming more common. Facebook, Twitter, WhatsApp, and Instagram have become very popular in the recent decade [1]. Social media (SM) can swiftly broadcast information far and wide, allowing users to see and learn about events occurring far away in space and time. Many people know that some of the information on social media is not entirely true [2]. Indonesia has had several natural calamities recently, but flooding is the most popular subject on social media. Users are compelled to post photographs or update news from the region impacted by the Flood to SM to convey the current situation. Due to the interaction process, individuals utilize the information as a reference to determine their attitudes and decision-making for the benefit of the victims of catastrophes, who can track and monitor the catastrophic occurrence more easily [3].

Calamity management has played a critical role in reducing the number of people killed and the amount of property and infrastructure that has been damaged. Effective disaster management requires a complex system for collecting, integrating, managing, and analysing data from various sources, such as video streaming, sensors on the ground, and satellite images [4]. Social networks and crowdsourcing have allowed human-centric techniques that permit the public to offer critical information to improve crisis management and reduce natural calamity impacts [5].

Computer, geographic information science, and domain science researchers can learn much from social media data [6]. By 2020, 3.5 billion people will use social media, almost half of the world's population. Social media creates a broad range of data, including text, photos, videos, and vast amounts [7]. Natural disasters have a considerable influence on people's physical and mental health. This includes injuries received, exposure to weather dangers, deterioration of inadequate sanitation, and contamination of water supplies [8].

Social media can have a big effect on natural disasters, and the study aims to give basic tips for coordinating communications and sharing information among people in these situations.

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1.1 Social media environment of calamity

Digital media innovation transformed Public Service Obligations (PSO) communications globally [9]. Businesses are increasingly relying on Facebook and Twitter as part of their online strategy because of the ease with which authors can connect with customers and other stakeholders [10]. Instead of relying on a one-way public information approach, social media allows PSOs and people to converse more in-depth [11]. Social media has also made it easier to connect creatively with journalists [12]. Disintermediation is the goal of disseminating information that promotes ethical values like honesty, openness, and faith in institutions [13].

Several academics have talked about the possible benefits of social media, such as making the government more open and accountable and making it easier to use public services. Studies have examined how social media could make people more likely to vote, get them more involved in their communities, and bring democracy back to life in the modern world [14]. PSOs favor asymmetric and one-way distribution strategies despite the option of dialogically communicating with inhabitants [15]. The existence of official social media accounts administered by PSOs can be significant because it can counterbalance the information deluge generated during crises. It is possible to utilize social media ethically to prevent the spread of misleading information.

1.2 Natural Hazard and Impact of Natural Calamity

A hazard is a potentially dangerous incident that could endanger people and the places where they live. Table 1 displays the several types of natural hazards that can be identified, as provided by the Center for Research on the Epidemiology of Disasters (CRED). Many more geophysical hazards exist, including mass movements, tsunamis, earthquakes, and volcanic eruptions. Climatological hazards include thunderstorms, high temperatures, and fog [16]. Glacial lake outbursts, wildfires, and Drought are examples of climatological dangers. Floods, landslides, and wave activities are all examples of hydrological risks. As stated in CRED and summarized in Table 2, natural catastrophes and consequences or threats to bodily well-being: injury/death, affected/damage [17].

Table 1: Natural risks are defined and categorized [17].

Hazard	Classification	Definition	Calamity Types
Natural Hazard Types	Geophysical	Geological risk is a term that is frequently used interchangeably with danger that originates in the solid earth.	Mass movement, Earthquake, volcanic activity.
	Meteorological	Severe atmospheric and weather conditions that endure from a few minutes to a few days can produce a scary scenario.	Fog, Extreme temperature, storm
	Hydrological	Hazard is induced by the development, circulation, and circulation of fresh or salt water on the surface or subsurface.	Wave action, Landslide, Flood
	Climatological	Atmospheric climate change spans from seasonal to multi-decadal timescales.	Drought, animal accident, wildfire, Extreme temperature, glacial lake outburst
	Biological	The danger posed by contact with living creatures and their toxins or the illnesses they can spread. Examples include venomous animals' toxic plants, insects, and mosquitoes that transmit disease-causing agents such as parasites, viruses, or germs.	Insect infestation, Epidemic

Table 2: Impacts of Natural Calamities [17].

Term	Definition
Fatality	An estimated total of individuals died because of natural calamities.

Injured	People who have been directly affected by a disaster need medical attention due to physical injuries, trauma, or disease.
Affected	People who were wounded, homeless (those whose homes were destroyed or severely damaged and so need refuge during a disaster) and impact.
Damage	The level of damage done to buildings, farms, and cattle. According to the Emergency Disaster Database (EM-DAT), losses are assessed in US dollars ('000). An individual calamity's recorded figure correlates to the current value of the event's damage.

2. Literature of Review

The following study expands on the previous impact of social media during natural calamities. Several investigators explain their findings, as seen below.

Ramakrishnan et al. (2022) [18] analyzed the likelihood of social media usage by underprivileged populations by relying on knowledge of the digital divide and attribution theory. The data was gathered via a survey and analyzed using Partial Least Squares Structural Equation Modeling (PLSSEM). The study's findings show that underprivileged populations are less inclined to employ social media for disaster management. After the study, there was a lot of interest in using social media for disaster management. In addition, the essay offers both theoretical and practical consequences.

Dong et al. (2021) [19] evaluate disaster relief efficiency by evaluating social media data, such as public opinions on disaster reactions and demand for targeted assistance resources during various calamities. Comparing machine learning (ML) models based on accuracy and computational time is done to improve present decision-makers with the right model. People's use of SM to aid calamity relief in the face of similar natural calamities as Twitter continues to develop is examined. Investigators could use the findings in their work to better understand how to handle natural disasters, and the authors could use the information to help disaster relief organizations.

Poornima and Murugan (2021) [20] suggested a strategy called the Natural Disaster Resilience Approach (NDRA). NDRA uses the Advogato dataset, which has 51,127 edges and 6541 users. Ultimately, the comparison was performed exclusively among the suggested Advanced Sybil Node Prediction Method (ASYNPA) Tier-3 and the current Vote Trust system, and the graph is mapped to the false positive (FP) rate, considering the accuracy and recall metrics. The number of confirmed Sybils in ASYNPA was 3.49 percent greater than in Vote Trust, at 99.84%.

Kankanamge et al. (2020) [21] examine the level of interest generated by disaster management-associated social media platforms. The study used five indices, commitment, popularity, virality, usage, and engagement, to assess community involvement by different social media outlets. It looked at three states in Australia, and its research concentrated on the official Facebook and Twitter accounts of the emergency response agencies in each jurisdiction. The study found that social media would be a viable medium for capturing community information on disaster management, but it still needs to be used more effectively.

Niles et al. (2019) [22] examined Five of the most expensive catastrophes in the United States in the past decade via the Twitter lens. Twitter activity after disasters, including the prevalence of both broad and narrow terms linked to food security, is positively correlated with network size. According to the investigation, people were likelier to use Twitter in the lead-up to hurricanes and for real-time or post-disaster data following tornadoes and floods. People with medium-sized systems are most likely to share data throughout these crises, and in most instances, they do so more often than is typical, which is consistent across all account types. A kind of social contagion that relies on normal people rather than those with disproportionately large spheres of influence is occurring in catastrophes' aftermath. The findings provide insight into the kind of catastrophe knowledge and target groups that could benefit disaster interaction during catastrophic occurrences.

Lu (Lucy) Yan et al. (2019) [23] evaluated the impact of information sharing on disaster preparation, response, and recovery on social participation. The authors examined all the organization's postings and user comments for three weeks, during, before, and after Hurricane Sandy. This research also shows that aid agencies can better use social media in crisis management by incorporating it into their existing strategies. Even though relief organizations focus on teaching disaster victims about aid delivery, many users were interested in knowing about the volunteers directly. As a result, organizations should provide information geared toward contributors, volunteers, and victims.

Auzzir et al. (2018) [24] assessed the effects of natural disasters on Malaysian small and medium-sized enterprises (SMEs). Among Malaysia's small and medium-sized businesses in 2016, a poll was performed to determine the kinds of disasters that had happened and the effects. The poll was also used to assess the challenges faced by SMEs in coping with natural disasters. According to the study, natural disasters significantly influence Malaysia's SMEs, with floods being the most frequent. SMEs were given advice based on the findings to help them deal with the effects of natural disasters.

Murzintcev (2017) [25] suggested a way for data mining on Twitter to find tweets about a certain event. It provides a method for gathering event-specific hashtags using an automated system. Hashtags are useful identifiers for separating related instances that occurred simultaneously; therefore, the strategy outperforms keyword-based solutions in relevance. Disaster databases were consulted to locate an incident and determine its potential impact region. Other events, such as riots, festivals, and exhibits, can be retrieved using the suggested technique.
Yu Xiao et al. (2015) [26] investigated after-disaster geographical variability in the production of Twitter messages. The tweets can be divided into four categories: mass, material, access, and motivation (MMAM). The MMAM model was mostly validated by the empirical analysis of tweets about Hurricane Sandy in New York City. In forecasting disaster-related tweets, it was discovered that community socioeconomic indicators were far more relevant than population size and damage levels.

2.1 Comparison between Reviewed Literature

As can be seen in Table 3, a wide spectrum of authors applied the method and shared their findings.

Table 3: Summary of literature of review

Author	Methods and Model	Results	Future Scope
Ramakrishnan et al. (2022) [18]	Survey methodology to collect data and PLSSEM	The results showed that underprivileged areas had a low inclination to utilize social media for disaster management.	It would be necessary to conduct more investigations to demonstrate causality based on the data presented in the study.
Dong et al., (2021) [19]	ML	The suggested study method's practicality, validity, and insights toward improved catastrophe management.	A more effective way of analysis would be developed by combining the benefits of several ML models.
Poornima and Murugan (2021) [20]	NDRA	The number of confirmed Sybils in ASYNPA was 3.49% greater than in Vote Trust, at 99.84%.	In the future, the sybils would rise beyond the Vote Trust in numbers.
Kankanamge et al., (2020) [21]	Social media	The study's findings show that postings on social media that include visuals and interactive maps promote community involvement.	The study's findings provided important insights that enlightened policymakers' future steps to develop data-intensive catastrophe management procedures.
Niles et al. (2019) [22]	Twitter word analysis, Keyword time series, and Disaster selection and characteristics.	During various potentially catastrophic events, it's critical to consider the context and target audiences for catastrophe information and how to reach them best.	This kind of data would aid future disaster preparedness and recovery efforts, which could help reduce losses from recent catastrophes and improve resiliency in a changing climate.
Lu (Lucy) Yan et al., (2019) [23]	Five groups that reacted to Hurricane Sandy in 2012 are included in the data set on Facebook.	It was possible that the organization's social media operations could be improved to meet its users' demands and motivate them to engage with organizations.	The method might be used to study other social media sites, such as Twitter, in the future.
Auzzir et al., (2018) [24]	Business Continuity Management (BCM)	Recommendations for SMEs were made to help them deal with the effects of natural disasters.	The study would not go into greater detail on the function of BCM as an SME disaster management strategy, which would be examined in future work.

Murzintcev and Changxiu (2017) [25]	ML	Experiments have shown that the technique could identify different hashtag sets even when numerous simultaneous events with comparable consequences occur. It is more accurate and selective than the current technique.	Future studies would benefit from examining how a message's three coordinates are arranged about one another.
Yu Xiao et al., (2015) [26]	MMAM	In forecasting disaster-related tweets, neighborhood socioeconomic indicators were most relevant than population size and damage levels.	In future studies, ground truthing should be used to compare the information gleaned from social media with what is being gathered.

3. Background Study

Social media has become an important way to spread information about disasters, giving authorities and aid groups real-time data that can help them better manage disasters. Exploration in the area has not gotten the attention it deserves, and it's still difficult to get valuable data. The study's goals are to use data mining and social media analysis to find out how people feel about how disasters are handled and what they need after different disasters. 41,993 tweets cover many natural catastrophes, including their sorts, durations, and damages. Manually categorized tweets gather information on public perception, including the need for targeted supplies, satisfaction with public panic, and disaster response. Eight machine learning models are used to investigate public perceptions of natural catastrophes quantitatively. Data scientists compare the computational time and accuracy of several ML models to suggest the best appropriate model to the decision-makers. Social media's potential role in assisting victims of the same natural catastrophes that fueled the expansion of Twitter is being investigated. The findings in work show that the suggested exploration technique is feasible and valid, and it provides disaster relief organizations with new ideas for improving catastrophe management [27].

4. Problem Formulation

In the last decade, social media platforms like Facebook, Twitter, WhatsApp, and Instagram have grown in popularity. Communication and information exchange among users of SM platforms are becoming more common. Calamity management has played a critical role in reducing the number of people killed and the amount of property and infrastructure that has been damaged. The issue addressed in this section is how to respond to a catastrophe management situation. Warning/evacuation, search and rescue, immediate help, assessment of damage, continued support, and immediate repair or development of infrastructure are only a few of the parts that make up disaster response. The goal of the emergency response is to provide timely assistance that will save lives, improve health, and promote morale. The authors employed two strategies to address the problem: logistic regression (LR) and random forest (RF).

5. Research Objective

This caption contains quantifiable and feasible objectives that would be accomplished during research.
The following are the Research objectives:

- To use social media to accelerate and mechanize disaster resilience in the affected area.
- To address issues related to actual requests for assistance during disasters submitted on OSN (the online social network) and to complete disaster resilience procedures on time.
- To recognize reputable users and prioritize the applications for assistance in times of crisis so that authorities can take immediate action to assist those in need.

6. Research Methodology

This section defines the research methodology based on the impact of social media during natural calamities. The methodology is an amalgamation of ML and graphical user interfaces based on the web. Any information relevant to the disaster category is included in the message dataset in the scenario. After that, the system would prepare data, transforming the original data into something more usable and appealing to the end consumer. The dataset that is used for data preprocessing is trained using random forest, which is a supervised ML technique that is frequently used in organization and regression issues, and LR, which is a statistical analytic technique that predicts a binary conclusion, such as yes or no, based on past observations in a data set. Random forest and logistic regression datasets are stored in pickle files, a useful Python function that allows models to be preserved, reduces the time spent retraining and allows the distribution, commitment, and reloading of previously trained machine learning models. After all machine learning models have been saved in a pickle file, a data analysis based on datasets for message and catastrophe categories would be the next stage. After the machine learning process is completed, it can forward to the web-based graphical user interface. The user interface has an input field where a message with a few keywords can be entered. The algorithm then selects the relevant department after classifying the keywords according to criteria into a certain group or system.

6.1 Technique Used

This part discusses the methods used, like random forest and logistic regression.

- *Text Mining (TM) of Natural Hazardous Impact*

Text mining is getting useful and important information from text sources. Many different types of information, including text and video, can be found on social media sites like Facebook and Twitter. Text mining algorithms should be able to be used successfully in the context of text data for a broad range of applications. Text mining techniques are needed for various applications, including keyword search, classification, and grouping in social media [28].

Keyword Search: A collection of keywords is used to identify nodes in social networks relevant to a particular query in the context of keyword search. Keyword search is a challenge in which authors employ content and linking behavior to find solutions. The general concept is that text documents with the same keywords are linked together. Consequently, identifying clusters of social network nodes containing certain phrases can be helpful [29].

Classification: In the categorization challenge, each node in the social network is paired with a label. The objective of using these tagged nodes is classification. There are several algorithms available for classifying text only based on content. However, the existence of linkages often offers helpful cues for categorization. For instance, label propagation methods can be used with content-based categorization to provide better outcomes.

Clustering: Clustering produced is, therefore, of substantially higher quality. Authors must identify group nodes with similar material to solve the clustering issue. Linkage and content could be used for categorization purposes in various applications [30].

The technique the authors created, called text-mining of natural hazard impacts, enables us to automatically extract data on impacts from text corpora by using machine learning (ML) and natural language processing (NLP) technologies. An earlier prototype application served as the foundation for TM-Impacts [31].

Three complementary modules help compensate TM-Impacts. The first is applying unsupervised topic modeling to identify the text's primary themes. These could contain data on reaction and recovery as well as the effects of the event. The second module focuses on extracting information on certain effects using hand-crafted algorithms and pattern matching (e.g., traffic disruption and power outages). The last module expands on the second by training supervised ML algorithms like the support vector machine and RF to categorize unlabeled text input into impact types.

- *Random Forest (RF)*

Random forest categorization has been increasingly used by machine learning algorithms that try to find spam on social media sites. In artificial intelligence, it is one of the ensemble approaches used to improve the success and accuracy of machine learning algorithms. An RF technique could also help determine which independent variables are important and let the system choose which functions to use. Many studies already show its relevance in empirical investigation, which is determined to be ideal in terms of prediction accuracy when picking various choices for each shrub [32]. The information obtained from the trees is used to create the most accurate projections possible. A decision tree forest assures a more accurate outcome by containing many groups and alternatives, while a single decision tree has a single conclusion and a restricted range of groups. The approach adds the benefit of incorporating randomness into the model by picking the best feature from a pool of randomly chosen features. Regression and classification models for the dependent variables are shown in Figure 1 of the decision tree. Given that there are just two child nodes (binary tree), Scikit-learn utilizes Gini significance to calculate the relevance of each node in a decision tree:

$$_{j} = w_j C_j - w \quad (1)$$

Where, $_{j}$= the importance of node j

w_j = weighted number of samples reaching node j.

C_j = the impurity value of node j.

$(j|\ \ )$ = child node from left split on node j.

(j) = child node from right split on node j.

Where, $_{j}$ represents the importance of node j, w_j is the weighted number of samples reaching node j, C_j represents the impurity value of node j, $(j|\ \ )$ shows child node from left split on node j and (j) is child node from right split on node j.

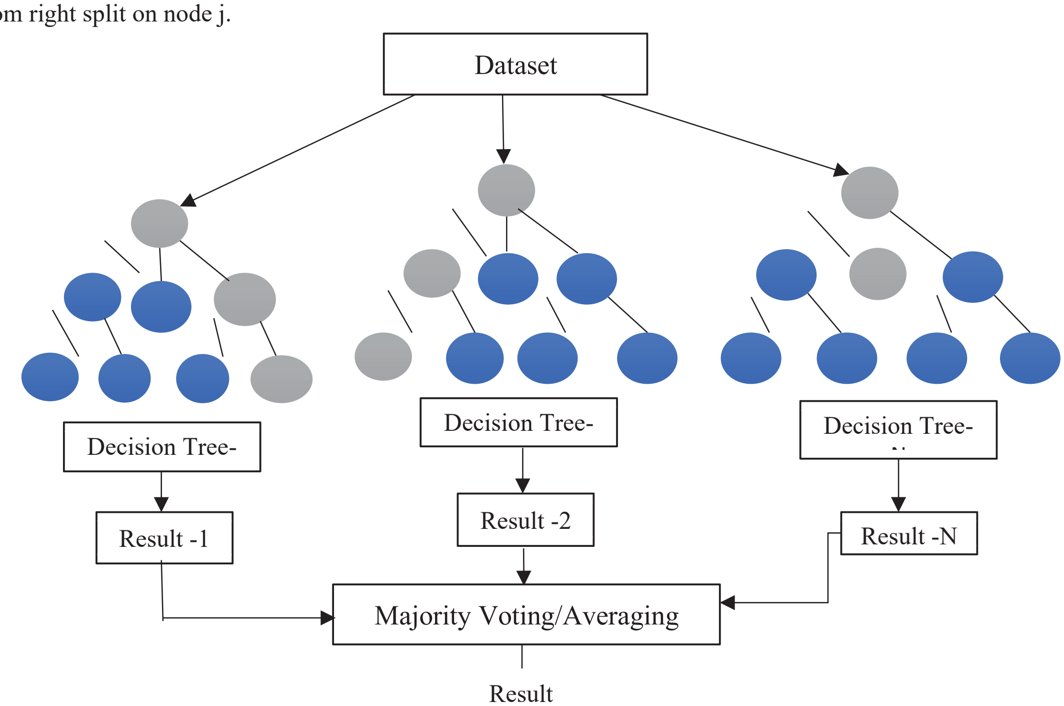

Fig. 1. The structure of Random Forest [33].

Algorithm 1 describes the RF algorithm [34].

Algorithm 1: The RF algorithm.

Training Phase:
Given:
-D: A training set with n instances, p feature, and target variable.
-K: range of classes independent variables.
-B: classifier counts in RF.
Procedure:
For $b = 1B$

1. It is possible to create a bootstrapped sample, D_b f by sampling from the training set, D.
2. Construct a tree using a sample D_b Obtained through bootstrapping.

For a given node t,

(i) Randomly select $m \approx \sqrt{p} \vee m \approx p/3$ feature.
(ii) Use a random selection of features to determine the optimal split feature and cutoffs.
(iii) Data with the best-split feature and cut points should be sent down.

The steps in (i)–(iii) should be repeated until the halting conditions are satisfied.

3. Construct trained classifiers C_b.

Test Phase:

Take the majority vote when combining the B trained classifiers. This is the expected class label from classifiers C_B For test instance x:

$$C_B(x) = argmax_j \sum_{b}^{B} I(V_b(x) = j)\,, forj = 1, \ldots\ldots, K$$

- *Logistic Regression (LR)*

Supervised learning can be included in the use of logistic regression. The formula determines the likelihood of a binary (yes/no) event. The categorical response variable and other variables are modeled using logistic regressions. In a logistic model, independent variables are combined linearly with log odds reflecting the chance of an event occurring. Binary LR estimates the likelihood of a characteristic of a binary variable according to the principles of the covariates under consideration. For the sake of argument, let's say Y is a binary response variable with uncorrelated data $Y_1, Y_2, \ldots., Y_n$, where Y_i=1 when the character is present and $Y_i = 0$when the character is absent. Consider the success probability to be π_i. A collection of illustrative variables that can be either continuous or discrete $x = \left(x_1, x_2, \ldots, x_p\right)$ as a set of variables [35]. Then, the logistic function for π_i is given by

$$log\pi_i = log\left(\frac{\pi_i}{1-\pi_i}\right) = \beta_0 + \beta_1 x_{i1} + \beta_2 x_2 + \cdots + \beta_p x_{i,p}; \quad (2)$$

Where,

$$\pi_i = \frac{exp(\beta_0+\beta_1 x_{i1}+\beta_2 x_2+\cdots+\beta_p x_{i,p})}{1+exp(\beta_0+\beta_1 x_{i1}+\beta_2 x_2+\cdots+\beta_p x_{i,p})} = \frac{exp\,(x'_i\beta)}{1+exp\,(x'_i\beta)} = \Lambda(x'_i\beta) \quad (3)$$

The probability that a sample falls into each of the two categories of the dichotomous response variable is denoted by the symbol π_i And it is obvious that $0 \leq \pi_i \leq 1.$ To estimate the parameters of a model, it can use the logistic Cumulative Distribution Function (CDF) $\Lambda(.)$, with $\lambda(z)\ e^z/(1+e^{-z}) = 1/(1+e^{-z})$ and β^s Signifies a vector of parameters to be assessed. The phrase $\frac{\pi_i}{1-\pi_i}$is called the odds ratio or relative risk [36]. Figure 2 indicates the schematic of a logistic regression classifier.

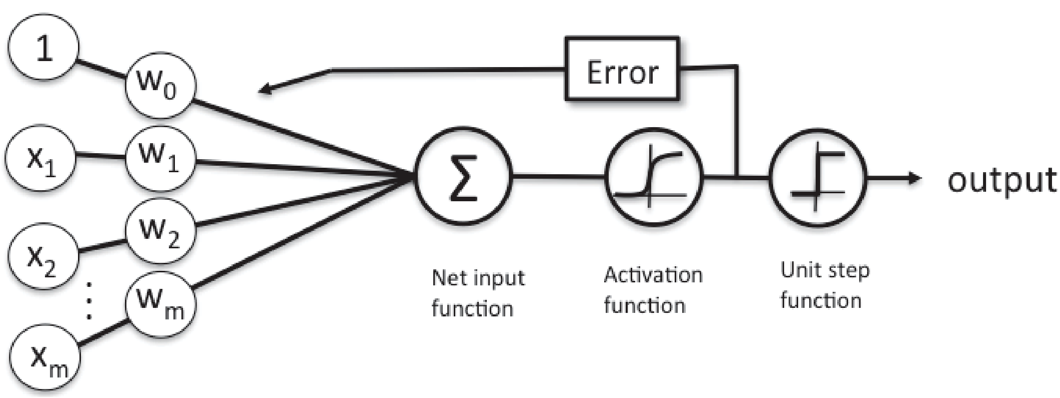

Fig. 2. Schematic of a logistic regression classifier.

7. Proposed Methodology

This section defines the methodology proposed based on the impact of social media during natural calamities, as indicated in Figure 3 below:

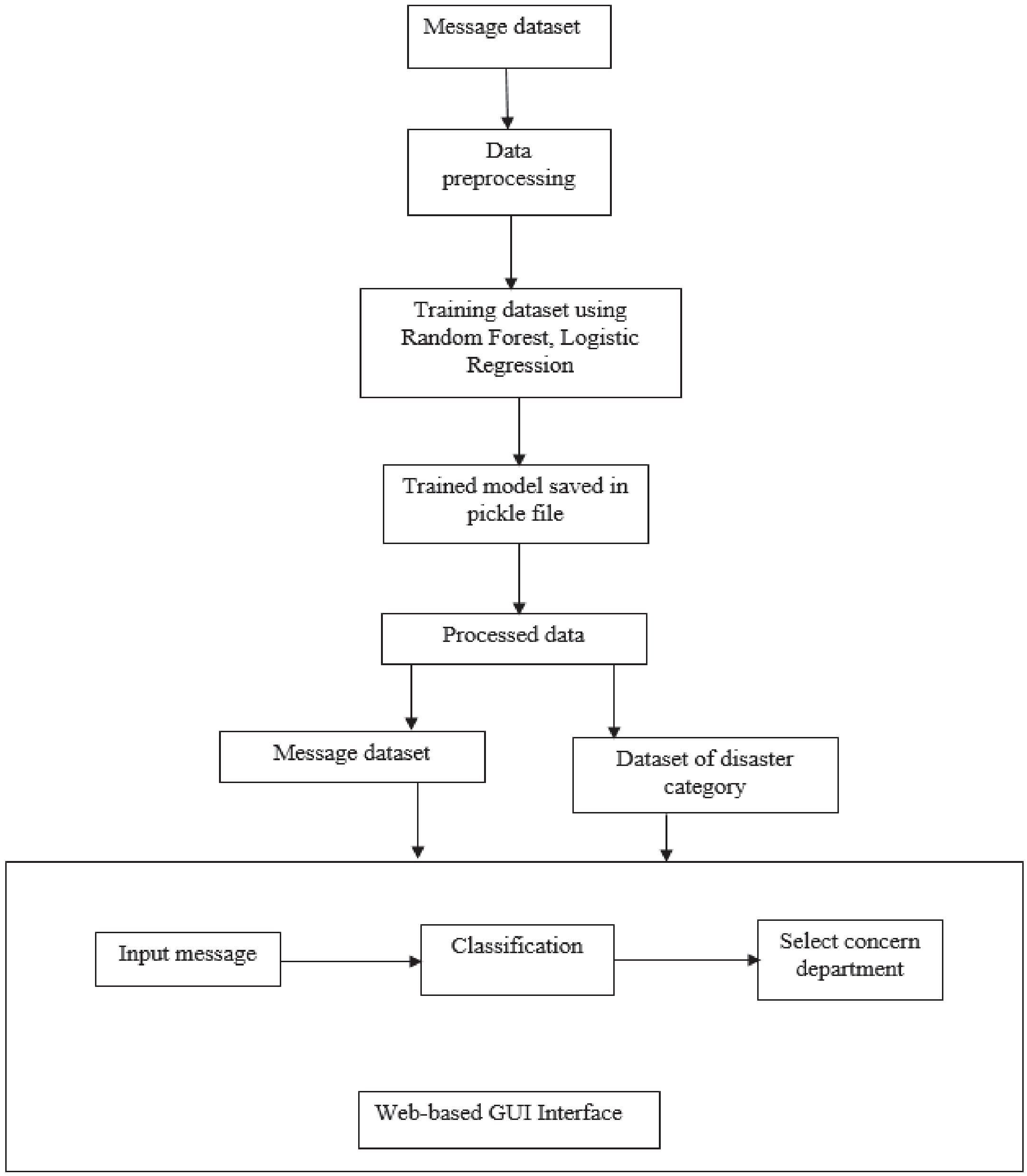

Fig. 3. Proposed Methodology.

Step 1: At this stage, any information about the disaster category is included in the message dataset.
Step 2: After the first phase has been completed, the program would do data preparation, changing data from the form it is in into a much more usable and desirable form.
Step 3: Logistic regression and random forest, two statistical analytic techniques, are trained on the dataset used for data preprocessing to predict binary outcomes, such as 0 or 1, utilizing prior interpretations of the data set. A binary result, such as 0 or 1, may be predicted using the statistical analytic technique of logistic regression by using earlier interpretations of a data set.
Step 4: Datasets trained using random forest and logistic regression are kept in pickle files, a helpful Python utility that enables the preservation of the models, reduces long retraining, and distributes, commits, and reloads pre-trained machine learning models.
Step 5: After storing each machine learning model in the pickle file, the next step is to analyze the data using the datasets for the message and catastrophe categories.
Step 6: After finishing the whole process of machine learning, it can now move on to the web-based graphical user interface. A message can be inputted in the user interface and includes a few keywords. The classification of

the keywords into a certain group or system based on criteria, after which the system chooses the concerned department.

8. Implementation and Results

This research predicts fraudulent behavior using an analytical model based on logistic regression and a machine learning technique called random forest with a constant random Gauss parameter.
The strength of the ties between the various logistic regression methods and the random forest containing a constant random Gauss is shown in Figure 4's correlation plot. A strong relationship exists between logistic regression and random forest, as shown by their high pairwise correlations.

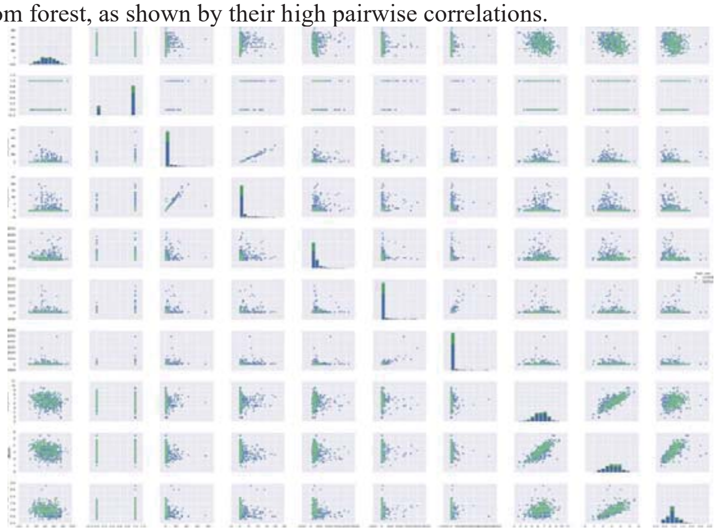

Fig. 4. Illustration of LR and RF correlation.

On the same dataset used to train and test the random forest model and the logistic regression model, the former yielded a higher positivity rate and the latter a higher accuracy rate and a higher precision rate, indicating that the latter was the superior method for detecting fraud. A comparison of the positivity rates of random forest and logistic regression in Figure 5 demonstrates that the latter yields superior results.

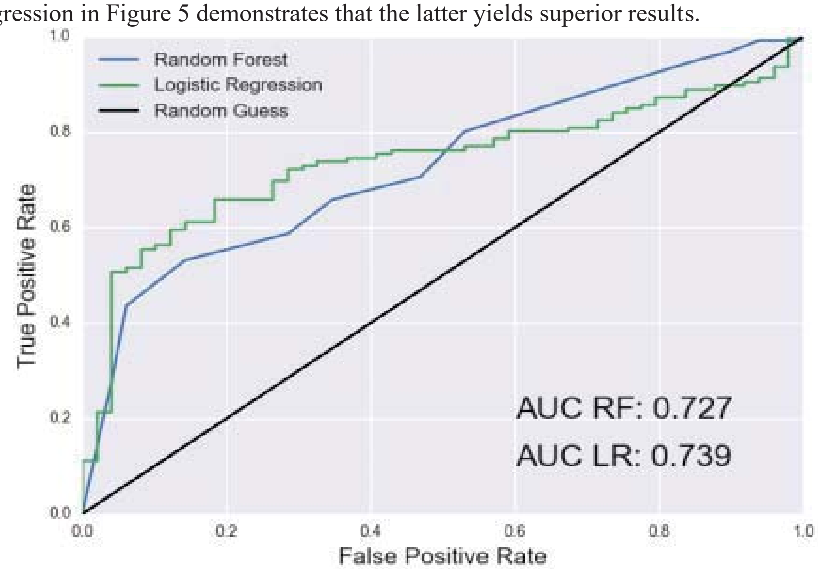

Fig. 5. Comparison of the accuracy of the technique used.

Pickle is a useful Python technique for storing random forest and logistic regression datasets because it keeps models, reduces the time needed for retraining, and makes it easier to share, commit to, and reload previously trained machine learning models. The accuracy of the LR and RF models is shown in Table 4. The reliability of the RF and LR models is shown in Figure 5.

Table 4 shows the accuracy of the models.

Models	Accuracy
Logistic Regression (LR)	73%
Random forest (RF)	72%

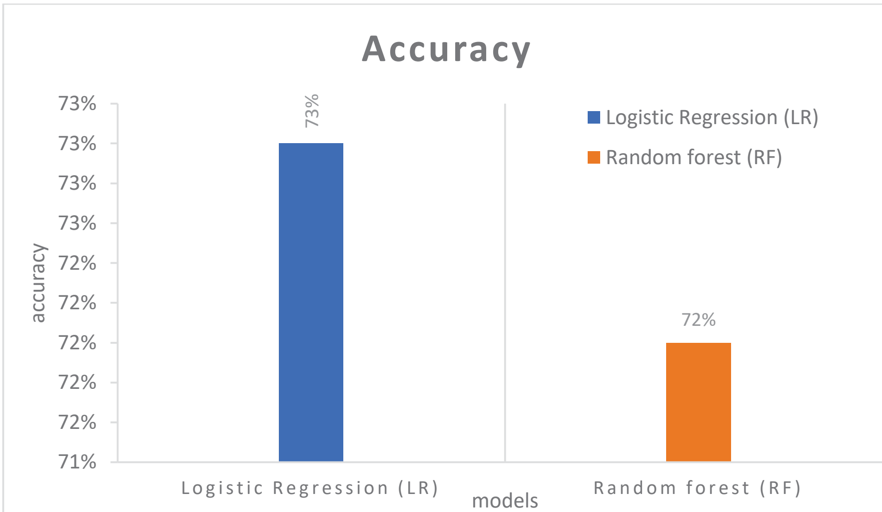

Fig.6. demonstrates the accuracy of RF and LR models.

9. Conclusion and Future Scope

During previous years, the use of social media had various effects on emergency management and disaster response. To better organize, manage, and enable a safe and predictable response to crises and catastrophes, crisis response professionals must recognize this influence, not as the unexpected result of an unmanaged calamity. This paper outlined the significance of social media, its goals, and how social media infrastructure has leveled the playing field for governments of all sizes. Examining systematic methods for using social media as a useful resource in disaster response allows us to explore the typical operational obstacles. Rapid assistance is provided in an emergency so that lives can be saved, health can be restored, and morale can be boosted. The authors used Random Forest (RF) and Logistic Regression (LR) to arrive at a solution. The accuracy results are shown in the accompanying graph. Therefore, disaster-related organizational learning and the minimization of the impact of misinterpretation can aid in the successful process management of diverse companies during calamities and assist in taking effective steps in case a comparable disaster occurs. Extending this research if false news influences anomalous consumer behavior during political choices is an area that needs more attention.

Further research on the impact of false news on different companies' branding is possible along these lines. The authors aim to employ a tweaked version of the naive Bayes method to distinguish between fake and legitimate news. By grouping users according to their online behavior and personalities, they may better identify which users are most likely to propagate the rumor.

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