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Identifying and Grouping Crisis-Related Social Media Posts for Disaster Response

S.Mahalakshmi
Ph.D. Research Scholar,
Vels Institute of Science Technology &Advanced Studies
Chennai, Tamil Nadu, India
mahamangai.vels6@gmail.com

R.Bagavathi Lakshmi
Associate Professor,
Vels Institute of Science Technology &Advanced Studies,
Chennai, Tamil Nadu, India
rbagavathi.scs@vistas.ac.in

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Abstract— Every year, within a specific timeframe, human society confronts challenges arising from natural calamities. The ultimate result of a natural crisis, such as flooding, hurricanes, earthquakes, and tsunamis, is the disruption of communication with the outside world. This communication disruption hinders individuals in the affected regions from accessing essential services, including medical care, sustenance, and potable water, potentially resulting in fatalities. Responders can also face difficulties in gathering information about the affected areas, which may be inaccessible after a crisis has occurred. Once the situation arose, the first two barriers were the breakdown of the power supply and communication to the outside world. Even though mobile communication is available, information is often obtained orally for a particular person, and this can lead to failure due to incorrect communication with the wrong number or the unavailability of the receiving party. Due to the introduction of smartphones and Online Social Networks (OSNs), information has been disseminated faster with the help of posting over available networks with low signal strength. Many people will see the posting and become aware of the situation in a particular area. This paper proposes a framework for identifying crisis-related posts with diverse topics and grouping them to disseminate information to responders, thereby facilitating a faster recovery process. A virtual group has been formed, comprising both requesters and responders of the same topics, and will exist until the last requester receives a solution for their need. The performance of the present work is also analyzed in comparison to the existing methods.

Keywords: ***Hashing Vector (HV), Coherence Frequency, Online Social Networks, Requestees, Responders, Information Dissemination.***

1. INTRODUCTION

Every year, within a specific period, human society dares to face the challenges arising from the occurrence of natural calamities. The occurrence of natural disasters, such as landslides, earthquakes, storms, tsunamis, floods, cyclones, wildfires, droughts, and extreme temperatures, can cause significant destruction to individuals and their properties [1,2]. The ultimate result of a natural crisis is communication disruption with the outside world. Once a natural disaster struck, the two immediate barriers that arose were the breakdown of power and communication with the outside world. Existing communication networks can be damaged by the occurrence of natural calamities, leading to communication interruptions and preventing the affected area from contacting the outside world [3]. Such a communication disruption hinders people in the affected areas from accessing essential services, including medical care, sustenance, and potable water, on the request side. The nature of the disaster may also result in the potential loss of life. Responders can also face challenges in collecting information from the affected areas.

Nowadays, most mobile services are active and provide communication in disaster areas. Moreover, with the advent of smartphones and OSNs, users can post messages targeted at a group of users, and the information is propagated within a limited zone. This may cause a delay in the recovery process and may lead to the responders taking actions in a delayed time interval.

This work presents a framework for identifying individuals involved in a natural catastrophe event by analyzing the topics of their posts in the Online Social Networks, with the help of hashing vectors and coherence frequency metrics. Upon computing the coherence frequency measurements, subjects are discerned, and users are subsequently categorised according to these topics for expedited information dissemination. A study has been carried out using a sample dataset, and the results are analyzed.

The initial section of this paper comprises an Introduction, while the subsequent section examines the review of pertinent literature. The third section of the study outlines the proposed approach, and the fourth section discusses the profound insights derived from analysing the selected datasets using the implemented version of the proposed framework. The final section includes the conclusion and prospective improvements of the current work.

II RELATED WORKS

Feng, Yu, et al. (2022) conducted a systematic review to grab and analyse natural crisis-related volunteer geographic information from social media posts [4]. Dong, Z. et al. (2021). They conducted an analytical study to enhance responses after a disaster. They work focused on analyzing the public sentiment characteristics by using Machine Learning (ML) principles [5]. Sufi, F. K., and Khalil, I. (2022) introduced a completely automatic system utilising Artificial Intelligence (AI) and Natural Language Processing (NLP) to abstract location-specific public attitudes in the context of a global crisis [6]. Mendon, Shalak, et al. (2021) provided a general framework for conducting sentiment analysis of users using a Twitter dataset containing details of the 2018 Kerala floods [7].

Huang, Lida, and others (2022) developed a new method to detect emergencies early on via OSNs. The methodology used text categorisation linked to emergencies, information regarding the 3W features (What, Where, and When) and the clustering of emergency incidents [8]. Zou, Lei, et al. (2023) analyzed the use of Twitter for emergency saving operations during Hurricane Harvey in the Houston and Beaumont-Port Arthur metropolitan statistical areas [9]. Karimiziarani, Mohammadsepehr, and Hamid Moradkhani (2023) examined a larger set of tweets about a hurricane that occurred in the US during September 2022 and identified how people used Twitter for disseminating posts during the occurrence of the crisis event [10].

Gu, Mingyun, et al (2022) surveyed a well-known social networking topic in China during COVID-19 to analyze the emotive changes of users [11]. Li, Hongxing, et al. (2024) examined the potential application of social networks concerning urban rainstorms and flood disasters [12]. Boota, Muhammad Waseem, et al (2024) investigated the spatiotemporal patterns of public responses to urban floods in Karachi in 20222 [13]. Al Momin, Khondhaker, et al. (2025) studied the behaviors of users into six unique classes during disaster events [14]. Su, Sini, et al. (2025) did a study based on compassion and dual-oriented system theory, investigating the issues and methods that affect the propagation of information about help during disasters, utilizing data from the 7.20 Henan Rainstorm event on Sina Weibo [15].

Andersen, Nina Blom, et al. (2025) investigated the application of crowd-sourcing principles and lively social-listening to improve the bonds between responders and individuals in need [16]. Cantini, Riccardo, et al. (2025) developed a novel method, termed Large Language Models (LLMs), which analysed a larger volume of user-generated posts, identified issues reported by affected individuals, and enhanced the recovery process [17]. Tamer, Zekiye, et al. (2025) emphasized the necessity for timely and accurate information distribution and developed a decision-making model to facilitate flexible and rational choices by authorities [18]. Majemite, Michael Tega, et al. (2024) initiated an exploratory investigation to elucidate the complex function of big data in U.S. catastrophe mitigation and response, analysed via the perspectives of geology and business [19].

Balan, Seema, and P. Revathy (2025) analyzed the impact of technology on crisis management within educational settings and evaluated the tools, platforms, and practices in the field of digital that are essential for crisis response [20].

The literature review emphasizes the importance of social media in disaster management, particularly in terms of information dissemination and crisis response. Numerous studies have utilised social media data to assess public sentiment, detect emergency events, and support rescue operations. Social media platforms are employed to gather disaster-related information, identify emergencies, and distribute essential information during crises. The highlighted related works emphasize the variety of social networks platforms and analytical methods utilised in disaster handling research. Researchers have utilized Twitter, Sina Weibo, and other platforms to study public reactions to natural disasters, including hurricanes, floods, and rainstorms.

Additionally, research has employed a range of machine learning and data analytics terminologies, such as text categorisation, clustering, and sentiment analysis, to derive insights from social media data. The results of these studies highlight the significance of social media in improving disaster preparedness and crisis response, establishing a foundation for future research in this area.The present research proposes a model for identifying requesters and responders using a topic-based model, aided by a hashed vector and coherence frequency measurement.

III. PROPOSED METHODOLOGY

The primary objective of the present work is to identify users' posts related to natural calamities based on hidden topics within the posts and form a virtual group for a faster recovery process. The users might be either the requesters or the responders who offer services to those in need. The overall proposed methodology is presented in Figure 1.

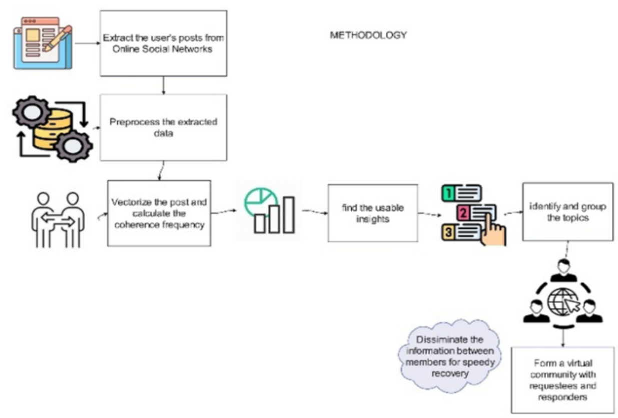

Fig 1: Overall Proposed Methodology

The first phase of the present work is illustrated in Fig. 1, and involves extracting the necessary data from an OSN. The present work extracted 20,000 users' posts from X.com (formerly known as Twitter) using a Python script.

In the second step, the extracted posts are pre-processed to remove the unwanted information from the original. After pre-processing, all purified data are vectorized with the help of the hashing vectorizer function, and the vectorized version is applied for the calculation of coherence frequency measurement.

Once the coherence frequency is calculated, the topics are easily identified, and users, including both requesters and responders, are grouped into a virtual group based on these topics. After the formation of the virtual group, information is to be easily disseminated to all users for a faster recovery process, and the group will remain in existence until the last user receives a solution. The topics are identified with the help of Latent Dirichlet Allocation (LDA) topic modelling.

The overall methodology is implemented as a novel algorithm named Disaster Topic Finder (DTF) to identify topics from users' posts on OSNs. The entire algorithm is represented in the Table. 1.

Algorithm Disaster Topic Finder (DTF)

Input:
D: Set of disaster-related posts extracted from OSN
n: Number of topics to discover
α, β: Hyperparameters for LDA
k: Number of features for hashing vectorizer
Output:
T: Set of discovered topics
G: Virtual group of users (requesters and responders) based on topics

Step 1: Preprocessing
Tokenize each post d_i into individual words or tokens: $d_i = (w_1, w_2, ..., w_l)$
Remove common stop words (e.g., "the", "and", etc.) from each post
Apply stemming or lemmatization to reduce words to their base form
Represent each post as a vector of word frequencies: $v_i = (v_{i1}, v_{i2}, ..., v_{ik})$

Step 2: Vectorization and Topic Discovery
Vectorize the preprocessed posts:
$$V = \{v_1, v_2, ..., v_m\}$$
Apply LDA to the vectorized posts:
$$T = LDA(V, n, \alpha, \beta)$$
Calculate the coherence frequency for each topic: $CF(t_i) = (\sum(\text{co-occurrence frequency of words in } t_i)) / (\sum(\text{total frequency of words in } t_i))$

Step 3: Virtual Group Formation

Group users (requesters and responders) based on their topic interests: G = GroupUsers(T, D)

Let $G = \{g_1, g_2 ..., g_n\}$ be the set of virtual groups

Step 4: Output

Return the set of discovered topics T and the set of virtual groups G. The extracted data are pre-processed by removing unwanted characters and symbols. Moreover, the retained individual words are converted into their base form using stemming. After preprocessing, the hashing vector for each word is calculated in step 2. Then, LDA is applied for topic discovery, and coherence frequency is calculated for each found topic. In step 3, virtual groups are formed that contain both requesters and responders. In the final step, the set of found topics and the virtual groups are returned for faster dissemination of information.

IV RESULT ANALYSIS

The central concept of the present research work is to identify hidden topics in users' posts on OSNs. The presented algorithm DTF is shown in Table 1 of Section. 3 is implemented by using a Python script. Before that, a sample of 20,000 users' tweets is collected from X.com, using the tweepy library, and a set of samples is taken for the analysis process.

A sample of the extracted data is depicted in Figure 2. The data shown consists of two columns: created_at and text. The created_at field contains details about the date and time of creation, as well as the username of the user who created the post on X.com. The text contains the information about the relevant contents given in the search term. Moreover, the text part of the dataset includes some irrelevant characters, symbols, and emojis that are not necessary for further processing.

	created_at,text
0	2025-07-13 04:35:35+00:00,"RT @nammavar11: Following the phenomenonal success of Ek dujhe ke liye renowned producers, big stars from Mumbai used to flood in large num..."
1	2025-07-12 09:38:27+00:00,"RT @Vignesh_tmv: BJP sangi moron Annamalai staged a funny drama by riding in a boat in a feet level water during recent Chennai flood.
2	His..."
3	2025-07-12 06:31:30+00:00,"@Suhelseth @DC_Gurugram @NayabSainiBJP these are learning in flood,usually chennai when there is heavy rain and water logging they switch off road side electricity supplies"
4	2025-07-11 16:14:02+00:00,"RT @nammavar11: Following the phenomenonal success of Ek dujhe ke liye renowned producers, big stars from Mumbai used to flood in large num..."
...	...
4846	Floods voche Time lo chennai Flyovers paina Cars Parking pedutharu akkada Janalu.. ikkada Swimming chesthunnaru ra https://t.co/Y7wCTMtlsi"
4847	2025-07-19 01:07:41+00:00,@praneethweather This is called short term floods .even in chennai some areas also faced the same kind of chaos for just 9-10cm of rains.
4848	2025-07-18 11:44:32+00:00,"RT @this_is_shibu: @kraman2 converting new assembly building to hospital, tried to convert anna library to hospital, highly grand party mee..."
4849	2025-07-18 11:20:23+00:00,"@kraman2 converting new assembly building to hospital, tried to convert anna library to hospital, highly grand party meeting in thiruvanmiyur 2015 just after chennai floods with banners and posters all over, felt insensitive and kind of careless to feelings of people who suffered"
4850	2025-07-18 06:53:34+00:00,"@bby2k @DineshKumar_TVK @sumanthraman Yes, Parandur is ~70-80 km from Chennai's OMR IT hub, adding 1.5-2 hours commute, which could hinder economic integration. Tiruporur (20-30 km) is closer for convenience but was dropped over defense proximity, not floods. Padalam, at ~50 km, might balance distance and minimal"

Fig. 2 Samples from extracted X.com posts

The selected sample is applied to the DTF algorithm and then subjected to preprocessing to remove unwanted characters. Once the preprocessing is over, the purified details are shown in Figure. 3.

	created_at,text
0	nammavar following phenomenonal success ek dujhe ke liye renowned producer big star mumbai used flood large num
1	vignesh tmv bjp sangi moron annamalai staged funny drama riding boat foot level water recent chennai flood
3	suhelseth dc gurugram nayabsainibjp learning flood usually chennai heavy rain water logging switch road side electricity supply
4	nammavar following phenomenonal success ek dujhe ke liye renowned producer big star mumbai used flood large num
5	monsoon rain year great leveller city excused rain treated every city street equally discrimination
...	...
4846	flood voche time lo chennai flyover paina car parking pedutharu akkada janalu ikkada swimming chesthunnaru ra http co wctmtlsi
4847	praneethweather called sho term flood even chennai area also faced kind chaos cm rain
4848	shibu kraman conveing new assembly building hospital tried conve anna library hospital highly grand pay mee
4849	kraman conveing new assembly building hospital tried conve anna library hospital highly grand pay meeting thiruvanmiyur chennai flood banner poster felt insensitive kind careless feeling people suffered
4850	bby k dineshkumar tvk sumanthraman yes parandur km chennai omr hub adding hour commute could hinder economic integration tiruporur km closer convenience dropped defense proximity flood padalam km might balance distance minimal

Fig. 3 Pre-processed data

The pre-processed data only contains meaningful lexemes, and the most commonly occurring words are represented in a word cloud representation by using their counts in Figure. 4.

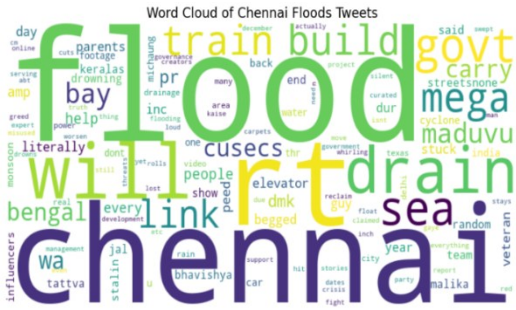

Fig. 4. Word Cloud Representation of pre-processed words

Each word shown in Figure. 4 is of a different size, indicating its maximum occurrence in the selected data. A word frequency density plot for the pre-processed words from the selected 5000 sample is visualized in Figure 5

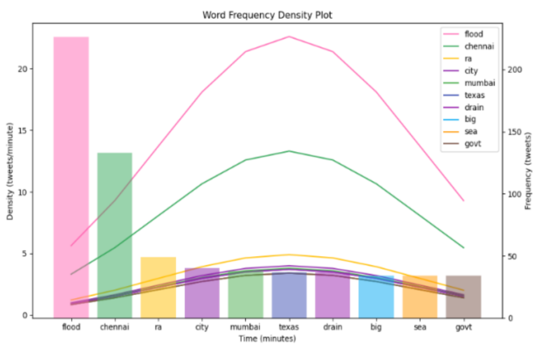

Fig. 5 Word Frequency Density Plot

The Word Frequency Density Plot (WFDP) illustrated in Fig. 5 shows notable trends employed in the sample. The bell-shaped curves mention the density of word frequencies and exhibit high symmetry, indicating an equitable distribution of words throughout the selected samples. The bar graph portrays the ranking of the ten most prevalent words. Certain terms, such as "Flood" and "Chennai," emerge as the principal themes.

Figure 6 also indicates a significant presence of unusual terms near the tail's end, suggesting that the dataset encompasses a diverse array of linguistic expressions. This visualization provides a clear insight into the foundational structure of the linguistic data, illustrating the significance of specific words and themes in relation to one another.

The distribution of WFDP is similar to a Gaussian distribution, but there is a major difference in the distribution, in that at certain points the curve is not uniform. Such asymmetry clearly indicates that, on these points, there are topics that are of lesser importance in the sample.

A sample of 15 topics, including their topic names, coherence frequencies, and scores, is represented in Fig. 5.

	Topic	Keywords	Coherence Score	Coherence Frequency
0	amp	amp, literally, stuck, inc, parent	309.8285	620.2296
1	voche	voche, flood, lo, time, video	288.3134	577.0889
2	velacherry	velacherry, real, content, updateschennai, child	288.4052	577.2702
3	pay	pay, abt, chennai, ahmedshabbir, seen	289.1943	578.8501
4	chennai	chennai, flood, hospital, faced, pay	297.1845	594.8520
5	co	co, lake, http, remember, qawx	291.3963	583.2634
6	ra	ra, submerge, avthai, kaadhu, erripooks	357.4854	716.2922
7	train	train, sea, maduvu, carry, tamilnadu	352.7478	706.9512
8	dmkprkumoneypeoplekusorry	dmkprkumoneypeoplekusorry, pr, chennai, every, drain	297.3316	595.1480
9	texas	texas, sumanthraman, flood, manikandanars, due	312.8781	626.3039
10	family	family, chennai, resettled, since, farming	292.6268	585.7264
11	http	http, co, chennai, flood, kerala	302.0472	604.5936
12	chennai	chennai, dmk, flood, year, monsoon	303.7202	607.9350
13	search	search, due, child, updateschennai, texas	304.4811	609.5377
14	flood	flood, help, hit, chennai, need	293.8405	588.1544

Figure 6 Topics, keywords, and coherence measurement.

The most frequent word is named as the topic, and subsequent words are included within that same topic, as shown in Figure 6. The corresponding topics, keywords, and weights are shown in Figure 7

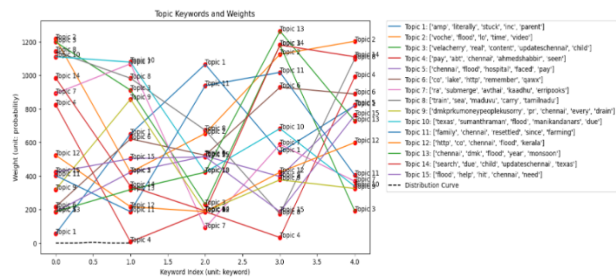

Fig. 7 Topics keywords and weights distribution

This plot, shown in Figure 7 displays the topic keywords and their corresponding weights for a topic modelling analysis, highlighting the top 5 keywords for each topic and their relative importance. The plot enables a visual comparison of topic keywords and their weights across different topics, highlighting similarities and differences between them.

The distribution curve serves as a reference point, and the plot can be used to analyze the importance of keywords within topics, identify patterns and relationships between topics, and gain insights into the structure of the topics. Table 1(a) and 1(b) shows a comparative evaluation of four crisis post identification approaches namely: TF-IDF + K-Means, Word2Vec + LDA, BERT-based Classifier and the proposed Hashing Vector-Coherence-Based Latent Dirichlet Allocation HV-CBLDA The comparison is done based on standard performance measures and they are Accuracy, Precision, Recall and F1-Score to measure the effectiveness of classification, Topic Coherence (C) to measure semantic interpretability of discovered topics and Processing Time per post to measure the computational efficiency as shown in table 1(a) and (b).. These metrics are taken together as an indication of the appropriateness of each method for real-time dissemination of crisis information in resource constrained and time critical disaster scenarios.

Table 1(a) Comparative performance analysis of crisis post identification and topic modeling methods

Method	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
TF-IDF + K-Means	78.6	76.9	75.4	76.1
Word2Vec + LDA	82.3	80.5	79.8	80.1
BERT-based Classifier	88.9	87.6	86.4	87.0
Proposed HV–CBLDA	91.7	90.9	92.4	91.6

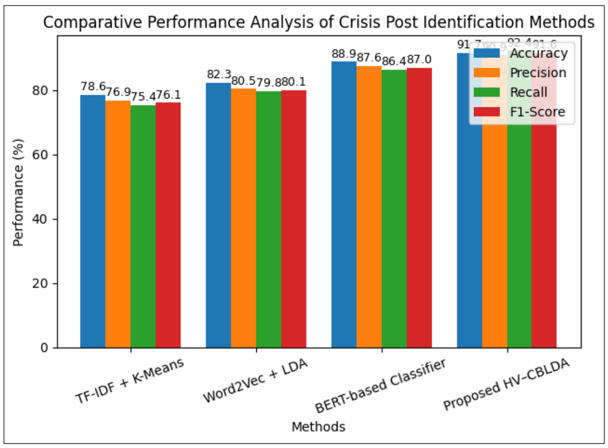

Figure 8. Comparative bar chart illustrating Accuracy, Precision, Recall, and F1-score of different crisis post identification methods.

From the figure 8, it can be seen that the accuracy, precision, recall and F1-score of the proposed HV-CBLDA method are better than all baseline methods. Its better recall and balanced performance signals the better identification of crisis-related posts and can therefore be adapted for reliable and timely information extraction in disaster response scenarios.

Table 1(b) Comparative performance analysis of crisis post identification and topic modeling methods

Method	Topic Coherence (C)	Processing Time (ms/post)
TF-IDF + K-Means	0.41	14.8
Word2Vec + LDA	0.52	21.3
BERT-based Classifier	0.58	68.7
Proposed HV–CBLDA	0.71	9.6

From the results, HV-CBLDA proposed framework can be seen to have better performance in all the evaluation metrics. It attains the best level of accuracy (91.7%) and F1 score (91.6%), which is more reliable and balanced crisis post identification than baseline methods. The recall of 92.4% demonstrates the success of this framework in detecting a higher proportion of critical posts related to crises which is important in reducing the missed requests for emergencies. Furthermore, the highest topic coherence score (0.71) attests to the fact that the extracted topics can be considered more semantically meaningful and interpretable, which allows for efficient grouping of requesters and responders. In terms of efficiency the proposed method also has the lowest processing time (9.6 ms/post) making it ideal for large-scale, real-time social media streams during disaster situations. In contrast, while boasting great accuracy, deep learning-based approaches such as BERT-based classifier is considerably higher for computations, which lesser positions for any of their deployment in any crisis area of low connectivity.

A. Discussion

The study analyzed 20,000 tweets related to disasters from X.com, aiming to identify hidden topics in disaster-related posts using a topic modelling technique. The analysis involved several steps, including preprocessing to remove unwanted characters and words, vectorization to convert text into numerical vectors, and topic discovery using Latent Dirichlet Allocation (LDA) to identify topics. The Disaster Topic Finder (DTF) algorithm was used to discover topics, consisting of four steps: preprocessing, vectorisation, topic discovery, virtual group formation, and output. The results showed that the DTF algorithm effectively identified topics related to disasters, highlighting the importance of social media during disaster events for effective communication and response. The study's findings can help authorities respond more effectively to disasters by providing insight into public concerns and perceptions. By analyzing disaster-related posts on social media, authorities can gain valuable insights into the needs and concerns of affected communities, enabling them to provide more targeted and effective support.

V CONCLUSION

This study proposed an intelligent framework for crisis information management, which makes use of ubiquitous usage of smartphones and Online Social Networks (OSNs) to overcome communication failure during natural disasters. By automatically identifying posts related to crisis, categorizing crisis-related posts into a diverse set of topical needs, and dynamically creating virtual groups of requesters and responders, the proposed system will allow efficient, many-to-many information dissemination under limited connectivity conditions. Unlike the traditional oral or person-specific communication mechanisms, the framework enhances situational awareness, minimizes misinformation and ensures critical requests for medical aid, food, shelter and rescue are visible to multiple respondents at the same time. Comparative performance analysis with existing approaches show that the proposed method has better accuracy in the identification of crisis posts, better grouping effectiveness and faster response co-ordination, thus contributing to a more resilient and response disaster recovery process. Despite being effective, the proposed framework points to a number of directions for future research. Future work can be on the incorporation of multilingual and cross-lingual analysis in order to support disaster affected regions with different language usage. The combining of real-time geospatial analytics and satellite data could further improve the prioritization of response according to the location. Additionally, the use of advanced deep learning models and transformer-based models may help to better detect implicit or ambiguous crisis-related posts. Privacy-preserving mechanisms and trust evaluation models will be studied for the benefit of the responders to ensure secure and trustworthy information exchange. Finally, the large-scale real world deployment and evaluation in actual disaster events would provide deeper insights on the system scalability, robustness and operational impact which would further increase the applicability in real world crisis management systems.

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