Study on Applications and Challenges in Natural Disaster Management using Multimodal System

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ABSTRACT

Organizations, which include government agencies, the military, and humanitarian groups, are responsible for providing the most vulnerable individuals with aid and protection during emergencies and disasters. Their rapid decisions are made possible through the information they gather. Their information needs vary depending on their specific roles and responsibilities. In times of crisis, they need factual and timely information, especially when there is a lack of reliable sources such as radio or TV. Due to the increasing number of people using social media platforms and mobile technologies, the general public has gained access to more effective and practical ways to share information. The term multimodal refers to the combination of various computational methods used to analyze the data collected from social media platforms. Some studies show how social media analytics can be used to summarize and curate information related to disasters. This paper discusses the research being conducted in the field of crisis informatics, which is an interdisciplinary discipline that combines the expertise of social science and computing to extract information related to disasters. Due to the availability of social media data, this field is heavily focused on developing effective strategies to use it.

Keywords: Multimodal System, Natural Disaster Management, Social Media, Machine Learning

INTRODUCTION

A natural disaster can have a significant impact on a community, as it can cause the loss of life and property. Effective management of disasters can help minimize the damage they cause. One of the most important steps in disaster management is preparing for emergencies. This involves developing plans to address the various risks associated with natural disasters. Preparedness also involves conducting awareness campaigns to inform the public about the hazards of disasters. Another crucial component of disaster management is deploying emergency personnel and equipment to provide immediate assistance to the victims of the disaster. This can be done through a disaster response team composed of government agencies, medical professionals, and first responders. Coordination efforts are also essential to ensure that the response is carried out efficiently[1].

In addition to providing immediate aid to the victims, natural disasters also require the establishment of recovery efforts, which are aimed at helping communities get back on track and rebuild their homes and infrastructure. This process can involve providing financial support, as well as supporting community groups' efforts to rebuild. Long-term planning is also important to prevent disasters from happening in the future.

In addition to helping prevent and prepare for disasters, technology can also help in the recovery and response to emergencies. Some examples of how this can be done include:

- Early warning systems: Satellite imagery, seismic sensors, and weather forecasting can provide early warnings of imminent catastrophes, which can trigger evacuations and other emergency responses.

- Communication and information management: Mobile apps, GIS mapping, and social media platforms can help improve the coordination and management of information during emergencies.

- Remote sensing and monitoring: Remote sensing devices, such as drones and satellites, can provide real-time information about disasters, which can improve the decision-making process and aid in the response.

- Emergency response and recovery: Autonomous systems, 3D printing, and robotics can assist in the recovery and emergency response efforts. These technologies can also provide vital services to the affected areas.

- Resilience and mitigation: Building resilient and mitigation strategies can be achieved through the use of technology. Some of these include flood barriers, early warning systems, and green infrastructure.

The technological advancements that have occurred in the field of natural disaster management over the years have helped to improve the efficiency of the response and the resilience of communities. One of the most important factors that can be considered when it comes to the development and implementation of effective natural disaster management strategies is the availability of multimodal systems. A computer-based system that handles and responds to various forms of verbal and visual communication, including videos, images, and text, is known as a multimodal system. These systems can interpret and provide output in different ways. Big data techniques that involve the use of multimedia information such as multimodal data collection, analysis, and visualization are useful in identifying and analyzing complex information. They can also help improve the development of disaster management systems. Unfortunately, implementing multimodal data fusion techniques is not easy for analyzing and understanding videos related to disasters. Many studies focused on the development of single-modal deep learning techniques instead of the challenges of multi-modal learning. But, in a multimedia system, the use of different data types can improve the performance of the system.

For instance, if there are missing values or errors in a few or several modalities, the system's final performance can be enhanced [2].

These can help improve the coordination of various aspects of the disaster response. Through the use of various communication methods, such as text, speech, and visual interfaces, multimodal systems can provide communities and individuals with the necessary information about emergencies. In addition to providing immediate assistance to those affected by disasters, multimodal systems can also help first responders manage their resources and provide them with situational awareness. For instance, by utilizing cameras and sensors, these systems can collect real-time data on the effects of disasters, allowing them to make informed decisions regarding the deployment of personnel and resources. Multimodal systems can also support recovery efforts. These systems can help with logistics management, community outreach, and damage assessment. They can also be used to visualize and assess the damage to infrastructure, and they can be used to interact with the affected communities through social media and other platforms [3].

Due to the increasing number of media types and the complexity of the data collected by the World Wide Web, the development of big data analytics has become a vital concern. One of the most challenging factors in the classification and detection of multimedia content is the amount of information that is required to be processed [4]. The rapid emergence and evolution of social media platforms such as YouTube, Twitter, and Facebook have created a huge amount of real-world information that can be used to identify incidents occurring in different parts of the world. However, the complexity of the collected data has become a major issue that needs to be resolved to effectively utilize it. In the case of natural disasters, such as hurricanes, huge amounts of audio, video, and text data are posted online. Unfortunately, it is very hard to find the most relevant videos for the users' interests [8,9].

This paper aims to review the literature on multimodal-based decision-making in disaster management. It will provide a comprehensive analysis of the various technological advancements that have occurred in the field of disaster management. It explores the potential challenges, opportunities, and applications that face this collaborative process in delivering effective and timely disaster management solutions.

RELATED WORK

The goal of this study is to develop a classification model that can extract information from social media data. The method utilizes LDA to identify the various subject information in the data. It then uses a combination of visual geometry group 16 and transformer representations to analyze the data. The classification of images and text data allows researchers to extract relevant information from the social media data during disasters. This study was conducted on Weibo data during a heavy storm in 2021. The findings of the study were compared with those of previous experiments. The accuracy of the study was 0.93. Compared to a KGE-MMSLDA model, it performed better by 12%. The findings of this study help researchers identify the various themes in natural disasters and make informed decisions during a situation [2].

The paper presents an advanced emergency management system (AEMS) that combines the potential of social media and smart sensors. It can collect and aggregate two types of data: user-generated content and data from the environment, which are collected through various social media applications and deployed smart sensors. The system combines the collected data to improve the efficiency and reliability of its various services. It can also identify the most critical areas and obtain useful information for emergency response. The results of the test scenario were encouraging. The data collected by the sensors and the citizen applications can provide a more accurate and comprehensive view of the disaster in L'Aquila. Some of the limitations encountered during the testing phase of the system prevented it from achieving more accurate results. These include the inability to retrieve audio and video registrations from the internet, as well as the use of a limited number of sensors. Other limitations of the system include the use of a single communication network to send data from the sensors to a remote control center, and the use of local networks for collecting sensor data [4].

The goal of this study is to develop a framework that combines the information collected from social media with image analysis to improve the performance of disaster management tools. The results show that the combination of text analysis and image analysis can improve the performance of certain image retrieval techniques [5].

The study tried to answer three related research questions. It proposed a methodology that combines multiple computational methods to extract visual and summary information from social media data. The results of the investigation were analyzed using massive amounts of Twitter data. The results of the study were analyzed using a mixed-method approach. The findings of the investigation helped technical experts and humanitarian organizations to improve their computational models and understand the information collected from social media during disasters [6].

This paper presents a method for identifying damage to cultural heritage caused by disasters. It uses data collected from social media, which is a noisy and timely source. We first examine the images posted by users of social media to determine their exposure to cultural heritage. They used a neural network to categorize the images. We then test the system against thousands of images from various sources, which exhibit the diversity of noise and colors typical of social media and the web. It can identify buildings, heritage objects, and non-heritage buildings that have been damaged by disasters and are intact. According to the results, the classification system can help reduce the manual work involved in identifying damaged cultural heritage by identifying relevant candidates. The results of this study are positive, as social media provides a quick and comprehensive view of the damage caused by disasters. Unfortunately, only a tiny portion of the images posted on social media show damage to cultural heritage sites. Unfortunately, it is impossible to find all of the images related to cultural heritage in the avalanche of images posted on social media. These methods can help minimize the number of images that a cultural heritage expert has to look through [7].

The paper proposes a set of methods that can detect sub-events in YouTube and Flickr data, which are important for understanding the situation. These methods are based on the use of textual annotations and other metadata. The findings of this study suggest that using social media and clustering in crisis management can help identify and resolve various sub-events. It does so without the need for manual monitoring. The results of the experiment show that the AC and SOM methods can provide a quick overview of the situation, while the 2PG and 2PGT methods are more user-friendly. The clustering method can also help emergency response personnel identify the various sub-events in social media data [8].

To effectively support the emergency response teams, automatic analysis techniques are needed. This paper aims to develop a set of methods that can identify real-time sub-events in the data collected from various social media sites such as YouTube and Twitter. The goal of this framework is to provide a variety of situational reports and summaries from the data collected from social media sites. It utilizes online clustering and online indexation to analyze the various sub-events that emerge from the data. Online clustering is a method that can update and detect the set of events in the data collected from social media sites. To test the framework, the researchers collected and analyzed the data from Hurricane Sandy in 2012 [9].

The paper presents a system that can analyze the visual information that citizens share on social media during an extreme event. It can then help the emergency management officials coordinate the actions and resources needed to respond to the situation. The system takes into account various factors such as the event class, the geographical area where the incident occurred, and the GPS coordinates of those areas. The system uses an SSD network to analyze the posted images and determine if they are related to the event. It then uses an image processing method to verify if the images are related to the geographical area of the emergency. The system's goal is to provide emergency officials with the necessary images to help them carry out their operations more efficiently. After a geo-validation procedure has been performed, the images can be used to quickly overview the incident. The ASMIS system can identify and validate the geo-location of photos taken in public spaces, allowing citizens to play a vital role in the emergency response. It can also help coordinate the activities of emergency personnel on the ground. The paper collected data from Twitter and paired it with Google Street View images, which provided geo-verifying information, to help coordinate the activities of volunteers and relief workers [10].

In the event of a disaster, city planners need to quickly identify and deploy rescue teams in the affected areas. Unfortunately, there is a lack of accurate information about the disaster zones and the presence of survivors in the debris. This paper proposes the use of image analytics in smart city infrastructure to improve response time. In this paper, a CNN model is introduced that can be used to identify the human body parts in the images collected from smart urban environments following an earthquake. The model was able to achieve an accuracy of 83.2%. The findings of this study suggest that the use of image analytics in smart city infrastructure can improve disaster response time. It also emphasizes the importance of rescuing trapped individuals in the affected areas [11].

The goal of this paper is to envision a Digital Twin framework that enables the convergence of the disciplines of crisis informatics and ICT in disaster management. It can also help improve the coordination and decision-making capabilities of various stakeholders. Through the use of AI, this framework can help improve the visibility into the dynamics of complex humanitarian and disaster management activities. The Digital Twin concept is a framework that can be used to improve the coordination and performance of various disaster management activities. It can be divided into four main components: data collection and analytics, multi-data sensing, game-theoretic decision-making, and network analysis. The current state of the art in the field of AI is analyzed and gaps are identified. This paper provides a theoretical framework for understanding the various aspects of the interdisciplinary field of disaster informatics and artificial intelligence. It also aims to establish a common vision for the research community. The findings of this paper will be used to develop a Digital Twin framework that can help improve the efficiency of disaster management. It will also help inform the development of AI-based techniques and methods for improving the management of disasters [12].

Through a combination of text and image information, this research aims to identify useful images from social media platforms for disaster recovery. The research utilizes a deep learning method to extract the various visual features from the social media data, and a Fast Text framework to extract the textual ones. The goal of this research is to develop a data fusion model that combines the textual and visual features of the data to classify relevant images for disaster recovery. Experiments with a real-world dataset, Crisis MMD, revealed that the model consistently outperforms the previous state-of-the-art by more than 3% [13].

The geo-referenced information collected about a storm's impact is very important for assessing its severity and helping to plan recovery efforts. Unfortunately, this information was not made available for several months due to the complexity of the assessment process. This issue affected the people in the most disadvantaged areas. The goal of this project is to develop a method that can estimate the impact of a disaster based on the collected geo-located content on social media. This method can be used by first responders and the general public to help with recovery efforts. Through a deep neural network, the prototype can provide a comprehensive assessment of the damages caused by the storm named Uri. A comprehensive performance analysis of the different geographical regions revealed that the trained model was able to estimate the damages caused by a storm in West Texas. This method can help promote social equity by helping the local communities get the resources they need to recover [14].

Due to the complexity of the disaster management process, it is often difficult to plan and implement effective responses. Emergency response planners must also carefully consider the allocation of resources to reach the most critical sites. Due to the complexity of the disaster management process, it is often difficult to make informed decisions. In this paper, image data is collected from smart infrastructures to improve the information available to emergency response planners. We use deep learning techniques to identify the survivors in the debris field using geo-tagged images.it is depicted that deep learning techniques are more accurate than conventional methods when it comes to identifying images. They also use less computational resources and time. The potential of image analytics to improve the efficiency of disaster response operations is evidenced by the findings of this study. It shows that the DL method can be used to help emergency response planners make informed decisions regarding the allocation of resources [15].

The paper proposes a method that uses unmanned aerial vehicles (UAVs) to identify flood-related features in images taken from a disaster zone. This method can help in assessing the damage caused by the disaster. The study area is located in Pakistan's Indus River, which is prone to flooding. Both pre and post-disaster images were collected by UAVs. In the training phase, the researchers created 2150 image patches by cropping and re-sizing the sources. These patches are used to train the CNN model, which is designed to identify and extract regions that have been affected by flood-related changes. The results of the tests revealed that the model was 91% accurate in identifying flood-related features. The researchers believe that the CNN model can help disaster management agencies identify the damages caused by a disaster and minimize the impact of the disaster on various assets worldwide. This method can also help in improving the smart governance of cities [16].

Getting the most accurate and timely information about a disaster's impact is very important to improve the management of the situation. This can be done through the use of airborne data acquisition tools such as drones and helicopters. One of the biggest challenges that this technology faces is the processing of large amounts of data. This process is usually carried out manually. In addition to this, it requires offline computing to perform properly. The goal of this study is to introduce and evaluate a set of CNN models that can detect ground objects in aerial images of a disaster. These models can recognize various types of ground assets such as damaged buildings and vehicles. The CNN models were trained on an in-house dataset known as Volan2018, which is a collection of aerial videos collected by drones and helicopters during the period from 2017 to 2018. Eight CNN models were trained using the YOLO algorithm. . They were then re-trained on the Volan2018 dataset and achieved an average of 80.69% and 74.48% in their classification for high and low-altitude images, respectively. The paper presents an extensive analysis of the variables that affect the performance of CNN models, such as the camera altitude, pre-trained weights, and data balance. It also shows that the models performed better when they were trained at similar heights than when they were tested at different altitudes. The models were also trained on a balanced drone video dataset and pre-trained on VOC, which resulted in faster training times [17].

When developing real-world applications, they usually encounter data sources that are different from one another. It is important to analyze all of the information that is collected from these sources to enhance the applications. Existing learning models tend to focus on a single modality, ignoring other data types. The paper presents a framework that combines the capabilities of deep neural networks to perform event detection in videos. First, it explores how these models can be used to extract valuable information from different sources. In this paper, a novel approach is proposed that combines the features of video and frame-level representations. It can perform a better analysis of the missing data type by taking into account other data sources. The framework is tested in a new video dataset with a set of natural disaster classes. The results of the experiments show that the proposed framework is more accurate than traditional fusion techniques and single-modality deep learning models [18].

This paper presents a decision diffusion method that can classify data related to various natural calamities such as earthquakes, floods, and hurricanes. It can perform better than text baselines in accuracy and image baselines [19].

The goal of this study is to develop a classification model that takes into account the various modes of information that users interact with on social media. The model can map the semantic content of the multiple modes into a unified text space. The classification model was then applied to various levels of social media data. Through a combination of deep learning and neural network techniques, the researchers were able to extract significant information features from the collected data [20].

The goal of this study is to develop a framework that can analyze and mine multimedia big data for disaster management. It takes into account the collected YouTube video dataset and then presents two deep networks that can analyze the various audio-visual elements in clips. The two models are then integrated using a fusion model, which takes into account the correlations between the various data modalities. The evaluation of the proposed framework is performed on a disaster dataset. It is compared with other fusion techniques and single-modality methods. The results of the study revealed that the fusion and visual model approaches performed well against the baselines. The proposed MCA-based model for multi-class classification performed well and had a final accuracy of 73% [21].

The summary of the review is depicted in Table 1

Study	**Multimodal Data Inputs**	**Key Technology**	**Advantages**	**Limitations**

[2]	Weibo data (Texts and Images) during the 2021 Henan heavy storm	Bert, VCG-16 and Late Dirichlet Allocation (LDA) for damage information	LDA is more flexible and adaptable to new data.	LDA is sensitivity to the number of topics and the quality of the data preprocessing.
[4]	Mobile social data, and smart sensors data	Big data Analytics using Machine Learning	Handle large volumes of data, identify patterns and trends, and make predictions and recommendations based on data insights.	The requirement for significant computing power and storage capacity ,Require a significant amount of labeled data for training
[5]	Image and associated text of social media	Bag-of-Words (BoW) and Speeded-up Robust Features (SURF), analysis of social media content using k-means clustering and Support Vector Machine (SVM)	Handle high-dimensional data, achieve high accuracy, and provide robustness to noisy or incomplete data.	SVMs can be computationally expensive, sensitive to the choice of hyperparameters and can require significant tuning to achieve optimal performance.
[6]	Textual and imagery content from millions of tweets	Random forest for relevance classifier, Principal Components Analysis (PCA) for feature summarization, K-means clustering for	Good accuracy, ability to handle various types of text, and the availability of pre-trained models.	Dependence on the quality and size of the training data

		humanitarian classification, and sentiment analysis using the Stanford sentiment analysis classifier		
[7]	Images posted on social media	Image categorization using convolutional neural network (CNN)	Learn complex features and patterns from raw data, enabling high accuracy in recognition tasks.	Sensitivity to overfitting
[8]	Flickr and YouTube data	Vector Space Model (VSM) for data representation. Self-Organizing Map (SOM),Agglomerative Clustering (AC), 2PhaseGeo (2PG) and 2PhaseGeoTime (2PGT) for identifying sub-events	SOMs able to reduce the dimensionality of complex data sets, capture nonlinear relationships between data points, preserve the topological structure of the input space, and their relative robustness to noisy or incomplete data. 2PG and 2PGT are able to identify sub-events within larger events, handle complex and heterogeneous data, perform real-time analysis, and capture temporal dynamics of sub-events.	The performance of SOMs can also be sensitive to the choice of initialization method and model parameters. 2PG and 2PGT dependency on the quality of data sources, the requirement of significant computational resources, sensitivity to model parameters, and difficulties with interpretability, particularly for complex events.

[9]	Social media data (i.e.,Twitter, Flickr and YouTube)	Online indexing using Standard incremental term frequency-inverse document frequency (tf-idf), "Learn & Forget Model" to identify important and non-important terms. Growing Gaussian Mixture Models (2G2M) algorithm to handle complete unlabeled data.	The advantages of tf-idf includes its simplicity, interpretability, and ability to handle variable-length documents. The advantages of GMMs include their flexibility, ability to model non-linear data distributions.	The tf-idf is sensitive to the size of the document corpus. the limitations of GMMs include their sensitivity to the initial choice of parameters and the potential for overfitting
[10]	Visual data produced and shared on Twitter	SIFT and SURF features extraction using advanced image processing and situational classification using deep learning	Ability to automatically learn features from raw data, handle large and complex datasets, and achieve state-of-the-art performance.	high computational requirements of deep learniing
[11]	Images from earthquake-hit smart urban environments	CNN model for classification	Refer [4] advantages	Refer [4] limitations

[12]	Information obtained from three sources: remote sensing, social sensing, and crowdsourced data collection	Artificial Intelligence (AI)	Increased efficiency, accuracy, and productivity, as well as the ability to process vast amounts of data quickly and identify patterns that humans may not be able to detect.	Inability to fully replicate human intelligence, leading to the potential for errors, bias, and ethical concerns.
[13]	CrisisMMD, a multimodal Twitter dataset	VGG16 model for image feature extraction,FastText model for text feature Extraction, Multimodal fusion for classification	Ability to provide a more comprehensive understanding of the situation	The need for advanced computational resources and expertise to effectively integrate and analyze data from multiple sources and modalities.
[14]	Text, Image, and Video of social media content	Deep Neural network for classification	Its ability to automatically learn features from raw data, handle large and complex datasets, and achieve state-of-the-art performance.	High computational requirements and time-consuming to train deep learning models
[15]	Image data obtained from smart infrastructures	Machine learning techniques (SVM and ANN), and Deep learning techniques (CNN, ResNet50, InceptionV3, and AlexNet) for	Refer [2] and [4] for advantages SVM and CNN	Refer [2] and [4] for limitations SVM and CNN

		classification		
[16]	UAV-based aerial imagery	Convolutional Neural Network (CNN) to extract flood-related features	Refer [4] for advantages CNN	Refer [4] for limitations CNN
[17]	Volan2018 Datasets	CNN model to identify and map objects of interest on the ground in real-time	Refer [4] for advantages CNN	Refer [4] for limitations CNN
[18]	Hurricane Harvey related videos with the correspond ing text informatio n	InceptionV3 for deep feature extraction, SVM for image model, LSTM for audio model, CNN for video model	LSTM's Ability is to handle long-term dependencies and effectively learn from sequences with gaps and irregularities. Refer [2] and [4] for advantages SVM and CNN	The limitations of LSTM include its high computational cost and memory requirements, making it challenging to train on large datasets.Refer [2] and [4] for limitations SVM and CNN
[19]	Multimoda l Twitter Dataset for Natural Disasters (CrisisMM D)	Transfer learning using VGG-19 for classification	It reduces the need for large amounts of labeled data for training a model from scratch.	High computational requirements

[20]	Text, image, and sound samples dataset implied the news public opinion corpora in Weibo, Wechat, Twitter, and Facebook	BiLSTM-Attention CNN-XGBOOST ensemble neural network model to acquire extensive multimodal information	Ability to handle both image and tabular data	Its computational complexity, making it computationally expensive to train and deploy, especially on large datasets.
[21]	Video dataset of natural disasters from YouTube.	Deep networks including a temporal audio model and a spatio-temporal visual model for content analysis and mining	Refer [11] for advantages of Deep Netowrks	Refer [11] for limitations of Deep Netowrks

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The process of managing natural disasters can be very challenging and complex. There are various factors that can affect its effectiveness. When a natural disaster hits, it can overwhelm emergency services' ability to respond immediately. This can result in a lack of resources that can hinder the recovery efforts in remote and impoverished areas. Communication is very important during a disaster, but it can be hard to maintain throughout the operation. Various factors such as infrastructure and communication networks can cause breakdowns, which can make it hard for the affected population to receive timely information. The rising severity and frequency of natural disasters are being attributed to climate change. This environmental phenomenon has also changed the weather patterns and created more intense and frequent storms. This can affect the response capabilities of emergency services. In addition to the physical effects of disasters, human behavior can also have an impact on the management of these situations. For instance, looting and panic buying can affect the response efforts of authorities. Political factors can affect the efficiency of the management of disasters. Issues such as the allocation of resources, the coordination of government agencies, and the prioritization of disaster response can be affected by these factors. Calamities can also be exacerbated by conflict and instability.

3. TECHNOLOGIES USED IN MULTOMODAL SYSTEM FOR NATURAL DISASTER MANAGEMENT

Multimodal systems for managing disasters involve using different tools and technologies to analyze, collect, and process data from different sources. Here are some of the commonly used ones.

- Geographic Information Systems (GIS): Geographic Information Systems (GIS) are computer-based tools that allow the capture, manipulation, and display of spatial data. They can be utilized to identify potential hazards, evaluate risk, and map natural disaster zones [12].

- Remote Sensing: Various remote sensing technologies, such as aerial photography and satellite imaging, can be used to capture images of areas affected by disasters. This data can then be used to identify damaged buildings and infrastructure [12].

- Wireless Sensor Networks (WSNs): A network of sensors known as wireless sensor networks (WSNs) can be placed in areas prone to natural disasters to monitor air quality, humidity, and temperature. The data collected by these networks can be used to issue warnings and identify potential hazards.

- Social Media Analytics: Social media platforms, such as Facebook and Twitter, can be utilized to gather real-time information about disasters, such as their location and severity. The data can then be analyzed to provide helpful information to the emergency response teams [4-21].

- Machine Learning: Large datasets can be analyzed using machine learning techniques to find patterns and insights that can help predict the likelihood of a disaster or mitigate its effects. For instance, these tools can help predict the likelihood of a flood event based on historical data [12,14,15].

- Augmented Reality (AR) and Virtual Reality (VR): Virtual and augmented reality (VR) headsets can be used to provide disaster response personnel with an immersive experience. They can also be used to test their response plans.

- Drones: Drone technology can be used by emergency response teams to collect vital information about disasters such as the locations of survivors and infrastructure damage. It can also deliver supplies and provide emotional support to individuals in areas where communication lines have been disrupted [17].

A multimodal system for managing disasters can integrate various technologies. The integration of these tools can help improve the efficiency and effectiveness of the response teams.

4. ROLE OF SOCIAL MEDIA ANALYTICS IN NATURAL DISASTER MANAGEMENT

For various reasons, social media analytics can be helpful in disaster management.

- Real-time monitoring: Through social media platforms, such as Instagram, Twitter, and Facebook, users can monitor the status of various disasters and identify areas of concern. This data can then be used to address issues that need immediate attention.

- Situational awareness: Through social media analytics, disaster management teams can gain a deeper understanding of a disaster's severity and location. It can also help identify the needs of the affected individuals.

- Public communication: Through social media, disaster management can communicate directly with the public. It can also identify messages that should be sent out to the public and gather feedback.

- Predictive analytics: Social media analytics can also be used to identify trends and patterns that can be used to predict the impact of disasters. For instance, by analyzing the data from social media platforms, disaster management can determine the path of a storm or the areas most vulnerable to flooding.

- Resource allocation: By using social media analytics, disaster management teams can allocate their resources more effectively to areas that need the most help.

Social media analytics can be very beneficial to disaster management teams as it allows them to make better decisions and respond faster to emergencies. Social media analytics can be very beneficial to disaster management teams as it allows them to make better decisions and respond faster to emergencies.

5. SOCIAL MEDIA ANALYITCS TECHNIQUES FOR MULTIMODAL DISASTER MANAGEMENT [2, 4-21]

Through social media analytics, disaster management can benefit from the processing of large amounts of data in real time to identify trends, sentiment, and patterns related to the disaster. Here are some techniques that can be used:

- Text mining: Through the use of text mining techniques, a social media post can be analyzed to find out what information is relevant to the topic, such as the keyword, location, and hashtags. This data can then be utilized to identify trends and patterns related to the disaster and its victims.

- Sentiment analysis: Social media posts can be analyzed through sentiment analysis to determine the sentiments of the users. This method can also be used to monitor the emotional state of those affected by the disaster and identify areas of concern.

- Network analysis: Through network analysis, it can be determined the connections between various social media users. This data can then be used to identify influential individuals and monitor the spread of news about the disaster.

- Location-based analysis: Social media users' location can be determined through location-based analysis, which can help track the disaster's spread and identify areas of concern.

- Image and video analysis: Videos and images posted on social media can be analyzed through video and image analysis to get a deeper understanding of the disaster. This method can also help track the progress of the response efforts.

Social media analytics can help disaster management teams make better decisions and improve their efficiency when it comes to responding to emergencies.

6. ROLES AND PROCESS OF ADVANCED MACHINE LEARNING IN SOCIAL MEDIA ANALYTICS FOR NATURAL DISASTER MANAGEMENT

Due to the increasing number of social media users, the data collected by these platforms has become a valuable source of information for disaster management. Unfortunately, the lack of effective analysis and utilization of the data has become a challenge. With the help of advanced machine learning techniques such as deep learning and NLP, it can be possible to automate the analysis of the data.

Through the use of NLP, which is a type of machine learning, it can be possible to identify the various keywords and entities in the social media data that are related to disasters. This can help in identifying the areas that are most affected by the disaster and providing useful information to emergency management officials. Another method that can be used to analyze the data is deep learning, which can help predict the impact of a disaster.

In the field of natural disaster management, machine learning can be used to develop early warning systems. This method involves analyzing the data collected by social media platforms and identifying the signals that could lead to a disaster. These systems can then inform the people in the affected areas to take immediate action.

Machine learning can play a vital role in the management of social media analytics in case of emergencies. It can help in analyzing and filtering the data, allowing emergency responders to quickly find vital information. In addition, these techniques can be utilized to develop systems that will alert individuals to take the necessary steps to protect themselves during a disaster.

When analyzing social media content for disaster management, there are several steps involved. The first step is to collect and preprocess the data related to the disaster. This process involves separating out the irrelevant content and performing data normalization and cleansing. Machine learning techniques are then used to analyze the data collected from social media platforms. These techniques can help identify the most relevant pieces of information about the disaster. For instance, they can analyze the text data to extract information about the disaster's location and extent. They can also analyze the audio and video content to extract information about the affected communities. The results of the analysis can then be communicated to the public and the emergency services. This can be done through the creation of interactive dashboards, which allow the public to explore the data. The use of machine learning techniques for social media content analysis can help improve the response time and provide support to the affected communities.

7. CONCLUSIONS AND FUTURE ASPECTS

Technological advancements have significantly changed the way disaster management is done. Through the use of advanced technologies, such as drones, satellites, and sensors, the ability to collect and analyze data related to natural calamities has been greatly improved. These tools can help identify areas of damage, monitor weather patterns, and assess the impact of a disaster. Data analytics and machine learning can be used to analyze and interpret the collected information, which can help guide the response efforts and provide helpful insights for the affected communities. One of the most important applications of modern technologies in the management of disasters is outreach and communication. Social media platforms and mobile apps can be used to disseminate information to the public and provide real-time reports on the status of the response efforts. They can also help facilitate two-way communication among the responders and the people in need. Virtual and augmented reality can be used to provide training exercises that are designed to help emergency personnel practice and prepare for scenarios involving disasters. Advanced technologies are becoming increasingly important in helping to manage disasters. These tools can provide faster and more effective responses to help the people affected by the disasters.

Despite the promising potential of multimodal systems for disaster management, there are still many research challenges that need attention.

- Integration of multiple data sources: The integration of information collected from different sources such as sensors and social media is a challenge faced by multimodal systems.

- Human factors and usability: The design of multimodal systems should take into account the needs of their users, such as emergency managers and first responders. User-friendly interfaces should also be developed to ensure that they can be operated efficiently in stressful conditions.
- Interoperability and standardization: Widespread use of multimodal systems requires they be able to work seamlessly with existing technologies and systems. This can be accomplished through the standardization of protocols and data formats.
- Scalability and resilience: A resilient and robust multimodal system is required to handle the immense amount of data that it collects and receives. This can be achieved through the development of efficient and robust architectures that use advanced computing techniques such as edge and cloud computing.
- Privacy and security: Privacy and security are two of the most important factors that must be considered when designing a multi-modal system. This is why it is important that the security protocols are designed to protect the sensitive data.

Addressing these issues will be vital to the success of multi-modal systems in managing disasters. These systems can help communities and individuals recover faster, save more lives, and reduce the damage caused by disasters.

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