Review:

Disaster Management Techniques by Deep Learning: A Review

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This article summarizes about the various methods/techniques based on deep learning available for predicting the likelihood of a disaster. Researchers have identified a number of disasters that can affect people, a few of them are volcano eruptions, floods, and earthquakes, etc. Convolutional neural network models are mainly used for post disaster management (i.e., analyzing the losses and damages). Damages occurred during a disaster are typically grouped into two categories: pre-disaster assessment and post-disaster assessment. The alerts regarding natural disaster prediction are performed during the pre-disaster assessment stage based on spatial and temporal information. But, during the post-disaster management, the losses are assessed (such as: damaged buildings or infrastructures) by unmanned aerial vehicles and drones. This will help to carry out the rescue operations. In literatures, deep learning has an important implication in catastrophe prediction and disaster management activities (such as: finding crowd evacuation routes and dealing with post-disaster scenarios). Some models used for natural disaster management are VGG16, LeNet5, VGG19, SEResNxt-50, and SPDA etc. This paper discusses about the pros and cons of various disaster management techniques. This will help the readers for developing an efficient disaster management technique.

Keywords: Deep CNN (DCNN), VGG16, VGG19, Pre-disaster managament ,Post-disaster managment.

1. Introduction

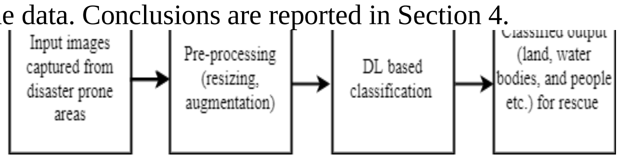
Natural and manmade disasters have become more common in recent years as a result of global climate change, infrastructure vulnerability, unplanned urbanization, and population development [1]. These above discussed alteration in nature affects the socio-economic condition of the affected area. Real-time geospatial data gathering and rapid mapping of degraded areas, along with rapid analysis of this data, play an essential role in reducing the negative social and economic repercussions of these conditions.

The manual pre-disaster and post-disaster techniques are slow and time consuming for identifying the damages due to flood, hurricanes, landscapes and volcanic erruptions. In the above-mentioned rescue operation is tedious and difficult. This current article mainly focusses on various approaches which are involved in the identification of pre-disaster and post-disaster using machine learning (ML) and deep learning (DL) techniques. Few of the popularly used DL techniques are VGG16, LeNet5, VGG19, SEResNxt-50, and SPDA etc.

Till date, many individuals have suffered significantly as a result of a lack of resources with a proper computational method which were used for disaster and pandemic management, that proved effective. It was impossible to foretell a calamity and extent of damage which was caused in a disaster-prone area. Post-disaster mitigation methods are not previously available, but the advent of various computational techniques in recent years has aided in evacuation and rescue operations. Major problem is the identification of various regions which are severly affected, loss of lives and amount of destruction which are caused where the traditional methods fail hence there is a need for use of DL techniques for image classification which provide better results in terms of performance of the models. The Deep convolutional neural networks (DCNNs) have made use of disaster prediction from the images captured and track the disaster scenarios. DCNNs have utilized various techniques for disaster identification process. In a few explicit disaster scenarios, pretrained models (such as: VGG16, and VGG19) were used for identification of hurricane. For post-disaster assessment management strategies, convolutional neural network (CNN) was applied for image classification in smart urban infrastructures [4]. Various segmentation algorithms (based on neural networks) have been used for aerial images. In case of hypothetical model, such as the digital twin paradigm, computer vision-based approaches [10] have been used for creating the simulated environment to that of natural disaster. Here, the method commonly used video footage for gathering data, data aggregation, and multi-actor game-theoretic decision making.

It is observed from various works that multi-layer perceptron (MLP) model has been used for flood forecasting [3]. It consists of input layer, output layer and hidden layer. Barring the input nodes, every other node is called a neuron which utilizes a nonlinear function for activation. Some other hybrid models such as bagging forest by penalizing attributes (BFPA), decorate forest by penalizing attributes (DFPA) that use bagging for flood risk assessment. Agent-based modelling (ABM) is applied to detect natural phenomena like wildfire land suppression and hurricane on large groups [19]. Few more models like risk assessment sentiment analysis (RASA) uses tweets and sentiment scores [22]. CNN architecture is used to train on internal visual data from hurricane Dorain regions for hurricane flood prediction [30]. Different models, like reccurent neural network (RNN) versions, are focused on sound classification in natural disasters [25]. Collaborative framework can be used to reduce on landslide images [27]. In this paper, various disaster management techniques have been discussed along with their advantages and disadvantages.

Disaster management using the different systems that can be utilized to carry out tasks like prediction, classification, and computer vision tasks can be represented using DL approaches. The remaining portion of the article is structured as follows: Various disaster management strategies are covered in Section 2. Section 3 discuses about the database used for disaster management and the website for downloading the data. Conclusions are reported in Section 4.



(a)

(b)

Fig.1: Steps for disaster management: (a) pre-disaster management, (b) post-disaster management.

Fig. 1 (a) discuses about the pre-disaster management where the input images are captured from disaster prone areas then preprocessing is performed using techniques such as image resizing and image augmentation techniques are employed. These images are used for deep learning (DL) based classification. Finally, the resultant output class is obtained as the region of waterbodies, land before disaster occurred (the actual images pre-disaster). In Figure 1(b) it has images which are captured post disaster images, various pre-processing resizing and augmentation is performed. The MUR rooftop images includes postdisaster and finally the images are classified to identify the disaster impacted areas.

2. Literature Review

Different studies that employ DL techniques (such as: Deep CNN (DCNN), and BERT models) are used for the pre-assessment and post-assessment of disasters during the scenarios such as: volcanoes, hurricanes, and earthquakes. Other types of disasters that occurred in various regions of the world that have used diverse methodologies. Various disaster management techniques available in the literature are discussed below.

Devaraj et.al (2021) [1] developed a model for hurricane disasters using DCNN. The architecture has used VGG19 with layers comprising 2D convolution layers, 2D max-pooling layers in addition to fully connected layer and output layer have been used for hurricane damage prediction. In the case of disaster prediction, there are two groups for damage prediction: training data for no damage class and testing data for damage class. A total 10000 images were equally present with damage class and without damage class. 20% images from each class have been used for testing and validation.

Parvathi et al. (2021) [2] developed a model for managing wildfire and flood using imageclassification task. The images were gathered from social media posts. The images were categorized into training (60,000 images) and testing (10,000 images).Kumar et al. (2021) [3] developed a data framework using the MLP classifier to depict monthly distributionof rainfall over a particular region in the Indian subcontinent. The model able to found the highest andthe lowest rainfall along with precipitation in a geographical region annually.

Chowdary and Bose (2020) [4] worked on the images obtained from the earthquake affected region of Central Mexico to detect the presence of people buried behind debris. Authors have used hot encoding technique to assign ‘0’ for representing the images without human body parts and ‘1’for presence of human body parts. The dataset was divided in the ratio of 80:20.

Daud et.al (2022) [5] focused on two different kinds of disasters such as flood and earthquakes by drones. They have classified the disaster management into four categories (such as: (a) planning or disaster administration, (b) exploration and saving lives operations, (c) transportation, and (d) training.

Cheng et al. (2021) [6] worked on videos obtained by five different drones for post-hurricane disaster management at Bahamas (from Great Guna Cay and Marsh Harbor). Three videos were captured with a resolution of 1280 x 720 and two videos were with resolution of 1920 x1020. All the videos have 30 frames/second. Here, CNN architecture was used for detecting building flaws.

Gupta et.al (2021) [7] experimented extensively on the satellite imagery data from the 2018 tsunami that affected Palu, Indonesia. The disaster impact assessment, compares satellite imagery before and after a disaster to find variations in roads and buildings. Authors have used a segmentation network to identify the objects in the pre-disaster and the post-disaster aerial images. The difference in expected road masking is used to update open-street-map (OSM) data in order to find accessible routes. Authors have dilated the buildings and roads in the segmented images with a tiny kernel (dimensions of 5 x 5) for several iterations for improved image resolution. The pre-processed images are cropped to 416 x 416 pixels, augmented (flipped horizontally and vertically), and normalized before training by the model. Images after the disaster were used for inference and assessment.

Moishin et al. (2021) [8] developed a model for flood forecasting. Authors have determined the research site's flood index (IF) by analyzing the previous 29 years flood data. A total of data points at daily time-steps was found to be 10,585. Antecedent IF and precipitation were treated as input parameters. Furthermore, 80 percent of the data was assigned to the model for training and 20 percent of the data being used for the model testing. Kim et al. (2021) [9] analyzed the natural disasters (such as: volcano eruptions, floods, and earthquakes, etc.) using DNN to estimate the financial loss on construction sites.

Chao et al. (2021) [10] used the model to identify natural disaster images from digital twin cities in USA. The model has used various categories of data (i.e., social media posts, volunteer, crowd sourced data, aerial images, maps, reports, and news articles). Jena et al. (2021) [11] used a CNN network to analyze the effect of earthquake (in the North-Eastern parts of India) and its categorization.

Pham et al. (2021) [12] used DNN to study the flood disaster in five basic steps (such as: (a) flood risk evaluation, (b) flood hazard assessment, (c) flood exposure assessment, (d) flood vulnerability assessment, and (e) flood risk map analysis). Authors have integrated the DNNs model and the multi-criteria decision analysis method to analyze the time series meteorological and streamflow data to updated river cross-sectional data.

Saja et al. (2021) [13] mainly focused on the natural disaster images (such as: floods, volcano eruptions, and earthquakes etc.) to access with social resilience. This method identified surrogates to assess social resilience and includes two key elements: (a) indicators selection for the surrogate approach, and (b) surrogate identification.

Aamir et al. (2021) [14] developed a multilayered DCNN for classifying the multispectral images obtained from flood, cyclone, and wildfires. The first block specified the occurrence of a natural disaster, while the second block specified its level of severity. The first block was made up of an image input, three micro convolutional blocks (each consists of four layers), and fully connected layers. The second block, was made up of three small convolutional blocks (each consists of two layers), an image input layer and the other is a fully connected layer.

Albrecht et al. (2021) [15] developed models that were focused mainly on geospatial natural disaster dataset collected by PAIRS geo-scope. This geo-scope is unique in two ways. First: it is the first commercial geo-scope to employ huge index raster data at the pixel level over a geographic and temporal platform. Second: the availability of hierarchical resolution levels that support numerous geographical and temporal resolutions, thereby linking the different layers of spatial and temporal data from geographical locations.

Ningsih et al. (2021) [16] evaluated the natural disaster data obtained from twitter to identify the specific incident (such as: earthquakes floods, and volcano eruptions). They used preprocess kgptalkie for data pre-processing. During the cleaning stage, email, URLs, HTML components, special characters, and duplicate characters were removed for disaster relief purposes. A TF-IDF feature matrix created from the raw document. It is therefore able to discuss the classifier in greater detail using LinearSVC. The default options for the class have been utilized. The settings could be customized to the classification's data content. Liu et al. (2021) [17] used SE-ResNeXt-50-32x4d model for identifying damaged building due to hurricane disaster dataset.

Eligüzel (2021) [18] worked on the tweets of ‘2015 Nepal earthquake’. Authors scrutinized over 7000 tweets regarding the earthquake. A total of 816 social media responses were acquired with the help of observing at certain topics including help, assistance, and contribution. URLs and punctuation were stripped from the data to make the data ready and understandable for further operations/applications. After the preprocessing stage, the tokenization procedure separated the strings into fragments. The

POS tag list was preserved in order to feed the RNN. The generic architecture for text engineering (GATE) software toolkit was used for analyzing.

Sridhar et.al (2021) [20] worked related to fire disasters (such as: forest fires, wildfires etc.). This approach used as a part of real-time fire detection scenarios. This method mainly used for tracking a huge housing building, profitable buildings, forests, laboratory, and vehicle fire in order to protect human lives. This plays a vital role minimizing the economic damage and environmental hazards. The process was tedious during the initial stage of firing, due to differing brightness level and occurrences of noise during collection phase. The fire forms a ring of colors (visible as red, orange, yellow and white along with of the rotation of particular frame along with varying dimensions of the frame).

Asimakopoulou et al. (2021) [21] work was based on collection of large volumes of disaster data in a collaborative manner, with major focus on crowd sourcing tools which can be enabled in smart buildings. It involved in the concepts of smart cities, where different participant users (such as: infrastructures, vehicles, buildings, and people) could be connected via different sensors and mobile APIs in order to collect data about their surrounding/neighbourhood environment. These collected informations and datas provided precise information about the disaster for analysis/management. The analysis was performed in a collective approach to provide a major edge when a disaster occurs. Data gathered from the crowd sourcing tools enables the planning and organizing actions based on real time scenarios for hypothetical environment. Post damage assessment involved various aspects such as emergency response operations with the data collected from sensors placed in vehicles, essential infrastructure, and buildings which monitored the conditions and would evaluate possibility of environmental disasters. The functionality offered, by the developed model architecture understood the need for remote access to the portal interface and the existence of a variety of remote participant users, including humans via their mobile devices and critical infrastructures, buildings, cars, and buses via their sensors. These users could access the interface, collect data from their immediate surroundings, and send it for analysis towards collective decision-making.

Parimala et.al (2021) [22] collected the data from social media posts about disasters and used a risk assessment sentiment analysis (RASA) algorithm based on people's sentiment. The importance of post-event emotions helped in determining the severity of the event (Ex: people were critical). Certain measures have been conducted on two factors: space and time. The method was divided into two stages: keyword creation from tweets and sentiment analysis based on significant events. The stages characterized the tweets with some meaningful term. These semantic words were then separated in the next phase to produce event-based words. For analyzing the preventive measures, a specific sentiment score consisting of information regarding a particular instance of time and location details have been computed. Authors have used the publicly available dataset called “social media disaster tweets-DFE”. Through the year 2015 across each month with different time period had total 629,365,000 records of tweets obtained from various parts and locations. The .csv file in the dataset contained many rows and 13 columns. The columns play a vital role in choosing-one keyword, location, and content all have an impact on the analysis. There were few columns that must be filled out in order to designate them as disaster-related or not disaster- related. Various works have categorized into positive, negative, and neutral tweets. Most of them are related to disaster and considered as “positive”. The rest are related to non-disasters and represented as “negative”. In case of binary classification there was one class called “neutral” and treated as negative, but could be considered as separate class in the case of multiclass classifier.

Munawar et.al (2021) [23] deployed a UAV to collect images from disaster zones and fed into CNN. The issues in this method associated with the retrieval of these photographs. These issues can be overcome with the use of images obtained from various online sources. These images were divided into two categories: pre-disaster and post-disaster. From the spatial details obtained, the two sets of information appear to be identical. In terms of time series data, there was a substantial difference. Many characteristics of images, such as edges and texture details, have been extracted using the convolution layer. The following attributes were learned from pre- flood and post-flood photographs to distinguish between pre-disaster and post-disaster images and classify them correctly. An activation function exists for each convolution layer. A ReLU activation function was used using convolutional layers. In large- scale photographs, pooling layers helped in minimizing the number of parameters, resulted in smaller images. As a result, the learning process became easier. To obtain the final classification output, the output from the previous layers was flattened and sent to the fully convoluted layers, which contained a softmax activation function.

Plata et al. (2021) [24] have worked on damaged unreinforced masonry buildings (MUR) roof top images caused due to earthquakes. They developed a technique which was capable of classifying street level images of an MUR with the help of rigid or flexible diaphragm. They used CNN for classifying the street level imagery of one-story level unreinforced masonry buildings according to the flexibility of the roof diaphragm (i.e., rigid or flexible). The data involves 1122 images that were collected from the metropolitan area of Medellin. This work was compared by various architectures such as VGG16, VGG19, InceptionV3, Xception and ResNet50. It was found that VGG19 architecture provided an accuracy, precision and recall of 80%, 88%, and 84%, respectively. The dataset was splited into training, testing and validation sets in the ratio of 60%, 20%, and 20%, respectively. The results were conducive and may help to decrease the financial and human resources needed to create detailed exposure models for unreinforced masonry structures.

Ekpezu et.al (2021) [25] developed RNN model based on sounds (i.e., both disaster sound and noise) for disaster management. Gude et al. (2020) [26] worked on floods by various DL architectures, which involved long short-term memory (LSTM) and auto regressive integrated moving average (ARIMA) models. The Gauge height data was collected from Meramec River in Valley Park Missouri to validate the model. The LSTM model was used to obtain gauge height when compared to ARIMA model. This dataset would help to detect the amount of water level in a particular region which was affected by flood post disaster assessment.

Iqbal et.al [27] have proposed a model on the landslide disaster that would have numerous limits along with the set of fundamental necessities connected with precise demands and issues at each stage of disaster management. A suggested solution must fulfil these needs at a minimum to be effective; however, due to challenges emerging from prior works, sufficient requirement formulation was found to be lacking. To address these problems, the authors suggested a set of disaster restrictions that were created to match solutions with disaster management criteria by taking Carter's concept and combining it with the proposed disaster management framework based on needs.

Sun et.al (2020) [28] developed a framework on different disaster such as flood, drought and landslide etc. There were four stages of disaster management (such as: mitigation, readiness, response, and recovery). The current work mainly emphasized on the summary of AI based approaches that facilitates various managing disasters at different levels. There were different tools which helped in the process. There were various applications discovered and focused on the disaster response phase.

Daud et.al (2020) [29] worked for post-disaster scenarios such as flood, earthquake, drought, wildfire etc. Authors have identified the disaster affected regions and rescuing corpses. The disaster victim identification (DVI) team had regularly experienced challenges related to corpse decomposition and identification. Despite the fact that this strategy used readily available conventional victim identification methods, that had previously been found to be ineffectual in acquiring victim information due to geographic location or disasters affecting inaccessible areas. It may be possible to eliminate DVI delays and the various issues that come with them using drone technology, rigorous people, and cooperation from necessary multidisciplinary teams, and evidence-based data.

Chung et.al (2020) [30] developed a model for hurricane aerial damage assessment of the buildings. They built and tested AI-assisted visual recognition models for post-disaster assessment using UAV data (PDA). An in-house dataset was produced using web mining and buildings visible in video frames that were manually labeled for different damage stages, and it was given an additional tag to indicate annotation information that was gathered in order to train AI models. The collection contained recordings of post-disaster scenes from Marsh Harbor and Great Guana Cay, in Bahamas. The method was trained and tested using annotated video frames from the first site. Zhang et al. (2019) [31] were able to develop an application for the phase of damage assessment. Post-disaster image data was used in these applications to evaluate the harm and the severity of the effects in the disaster-affected areas.

Shirzadi et al. (2017) [32] used a brand-new hybrid ML technique that investigated mapping of landslide susceptibility in the Bijar region of Kurdistan Province (Iran). The created approach used an ensemble of random subspace (RS) and Naive Bayes trees (NBT) to forecast landslides with an AUC value of 0.886. The model fared better than the NBT classifier, which had an AUC of 0.811.

Chaudhuri et al. (2020) [33] presented an efficient approach for classifying images from earthquake-damaged smart urban settlements. Authors used a DL technique (such as AlexNet, Inception-V3, and ResNet-50) to find survivors among the debris. Additionally, ML techniques like ANN and SVM were employed. According to performance evaluation findings, DL methods beat ML methods for classifying images. ResNet-50 demonstrated the best performance, scoring 90.81% for positive predictive value (PPV) and 92.05% for F1 score. Wahab and Ludin [34] used the ANN approach to estimate flood vulnerability assessment. RMSE and the determination coefficient (R2) were used to assess performance. The RMSE was equal to 0.0035, and the resulting R2 value was 0.996.

Sit et al. (2019) [36] mainly focuses on locating and examining the tweets related to the Hurricane Irma using natural language processing, DL, and ML techniques. This study's objective was to determine the services that are affected, the people who are impacted, and the infrastructure that is harmed. Based on location information and keywords, the authors used 500 million tweets that were posted before, during, and after the accident. The approach was successful in identifying the regions with severely impacted population and damaged infrastructure; therefore, the findings were encouraging.

Paul et al (2020) [37] analyzed Twitter data and the revealed the information related to power and communication losses, occoured due to seven significant hurricanes that struck the United States between 2012 and 2018. To exclude tweets about outages, a variety of ML models, including support vector machine (SVM) and logistic regression (LR), were applied. Additionally, they used transfer learning models like BERT to identify the different kinds of outages.

The brief description of the various existing works regarding disaster management techniques along with their corresponding performance metrics and data augmentation techniques are discussed in the Table 1 below. The dataset has been collected from various disaster affected regions of the world. There are two assessments performed namely pre-assessment and post-assessment in order to identify the amount of damage in particular locality or region and further various kind of loss of lives, damages to buildings etc. Various kinds of data augmentation were performed before training. In order to avoid financial losses, a few more models have been devised. According to the roof flexibility diaphragm, some models were developed using VGG19 on MURs.

Table. 1 Analysis of various disaster management techniques.

Title	Highlights	Results and discussion	Remark(s)
Devaraj et.al (2021) [1]: A novel DL model for tropical intensity estimation and post disaster management of hurricanes.	➢ DCNN is used for analysis of hurricanes. ➢ VGG19 was used for predicating weather conditions. ➢ They used multimedia sources like video database. Weather data automatically annotated over the videos. ➢ Identify various divisions specific to disasters such as hurricanes in order to perform post-disaster scenarios.	Dataset: HURDAT2 database (infrared satellite imagery dataset) confined to Atlantic and Pacific regions Performance: Accuracy - 97%, RMSE - 7.6%, MAE - 6.68%	Pre-assessment and post-assessments are carried out by transfer learning.
Parvathi et.al (2021) [2]: Disaster management using DL	LeNet5, VGG19, VGG16, and LSTM were used for classifying wildfire, and earthquake.	Dataset: MNIST dataset consist of 3460 images from the social media. Performance for VGG19, VGG16, and LSTM were: ➢ Training Accuracy: 84.52%, 87.69%, 80.7% ➢ Testing Accuracy: 76.39%, 83.6%, 73.14%	VGG16 performed better compared to VGG19 and LSTM.
Kumar et.al (2021) [3]: Flood disaster prediction using DL algorithm.	➢ MLP was used for flood forecasting. ➢ Predefined attributes were used for alarm warning disasters.	Dataset: Annual rainfall images from various regions of India. Performance: Accuracy - 97.40%, Sensitivity - 1.0, Specificity – 37.5%	Model detected flash floods in metropolitan areas and estimated annual rainfall risk assessment.
Chowdary and Bose (2020) [4]: Application of image data analytics for immediate disaster response.	➢ CNN was employed for image categorization in smart urban infrastructures.	Dataset: Consists of 3764 pictures collected from Central Mexico (in 2017 earthquake). Augmentation (rescaling, flipping, and	Accuracy was less than 90%.

		shearing) were used to increase the number of images. Performance: Accuracy - 80.37%, Precision - 81.21%, Recall - 79.53%, F1 Score - 8.033	
Daud et.al (2022) [5]: Applications of drone in disaster management.	➢ Drones were used for searching, rescuing, and transportation at the disaster location.	Dataset: UAV aerial images (Selangor Malaysia).	Disaster victim identification (DVI) was challenging due to the locating and retrieving of victims. Required more time for decomposition and identification.
Cheng et.al (2021) [6]: DL for post-hurricane aerial damage assessment of buildings.	➢ The SPDA model performed well in detecting damaged buildings in post assessment along with CNN that used cross-entropy classification loss.	Dataset: Consists of FEMA damage dataset (from Dorian, Bahamas). Data augmentation: performed by randomly transforming training images. Performance: Precision - 65.6%, Accuracy - 61%,	Damaged images were classified with high accuracy using a model based on two stacked CNN architectures.
Gupta et.al (2021) [7]: DL-based aerial image segmentation with open data for disaster impact assessment.	Segmentation techniques using neural networks were applied on pretrained aerial images with ImageNet for better performance.	Dataset: OpenStreet Map (OSM) data. Performance: Accuracy - 94.76% F1-Score - 73.98%	Classification of damages were identified in the completely destroyed infrastructures.

Moishin et.al (2021) [8]: Designing DL flood forecast model with ConvLSTM hybrid algorithm.	➢ A hybrid DL (ConvLSTM) method was used for disaster detection. ConvLSTM was made by combining CNN and LSTM.	Dataset used: Precipitation dataset, Fiji. Data augmentation is performed. Performance: RMSE - 0.279 Legate-McCabe Efficiency Index (LME) - 0.726	The algorithm considered two features. Effective forecasting and performance characteristics were used.
Kim et.al (2021) [9]: Development of model to predict natural disaster financial losses for construction projects using DL techniques.	➢ DNN was used to identify financial losses and steps to mitigate the financial loss.	Dataset: Data of company contractor all risk. Performance: MAE - 0.707 RMSE - 0.844	Enhanced risk assessment plan for building site could assist the Government in preparing for unforeseen situations like natural disasters.
Chao Fan et.al (2021) [10]: Disaster city digital twin: a vision for integrating artificial and human intelligence for disaster management.	➢ This work outlines a vision for a digital twin paradigm to enable interdisciplinary convergence in the field of ICT and AI for emergency management and disaster response involving data gathering, data integration and decision making.	Dataset: Disaster images were collected from crowd sourcing tools.	Disaster digital twin city paradigm can be used to integrate ICT tools for emergency response.
Jena et.al (2021) [11]: Earthquake risk assessment in North-East India using DL and geo-spatial analysis.	➢ CNN model was used for earthquake probability assessment in North-East India.	Dataset: Earthquake images were collected from North-East part of India (Assam, Mizoram, and Meghalaya)	Light detection and ranging are used to obtain high quality images from the earthquake regions.

Pham et.al (2021) [12]: Flood risk assessment using DL integrated with multicriteria decision analysis.	Hybrid models (ensembles of Bagging and Decorate) were used for flood risk assessment.	Dataset: Data collected from 847 past flood locations. Performance: AUC – 97.2% RMSE - 0.193	Flood risk map (prepared with consulting the local people) was used for assessing damages.
Saja et.al (2021) [13]: Assessing social resilience in disaster management.	Identifying acceptable surrogates for disaster mitigation social resilience indicators.	Dataset: Data collected by means of interviews with disaster practioners which includes rescue teams and their managers.	Data sources were used to examine potential surrogates discovered in the investigation on a local level.
Aamir et.al (2021) [14]: Natural disasters intensity analysis and classification based on multispectral images using multi-layered DCNN.	➢ Identified the disasters such as earthquakes, cyclones etc., by using DCNN.	Dataset: Total of 4428 natural images of flood, cyclone, and wildfires. Performance: Accuracy - 99.92% Sensitivity - 97.54% Specificity - 98.22%	Multilayered DCNN addressed the noise and serious class imbalance problems.
Albrecht et.al (2021) [15]: Next-generation geo-spatial temporal information technologies were used for disaster management.	➢ The rise of large data has upset traditional geographic information stores (GIS). ➢ Hence a spatial-temporal model has been devised to overcome the above-mentioned problem.	Dataset: Geo spatial image dataset from the New York city, USA.	This work uses a platform called PAIRS which is used to align the data using bigdata tools.
Ningsih et.al (2021) [16]: Disaster tweets classification in disaster response using bi-directional encoder representations from transformer (BERT).	➢ BERT used to assess the disaster from twitter data.	Dataset: Disaster tweets from social media Performance: Accuracy - 79% F1-Score - 0.75 Recall - 0.69	Model accurately determined the real disaster (target) from the non-real (non-target)
Liu et.al (2021) [17]: post-disaster classification of damaged building using transfer learning.	➢ Building localization was done using SE-ResNeXt-50-324d, and building damage assessment was made by HRnet.	Dataset: Online free xBD dataset Performance: Accuracy - 86% F1 Score - 0.65	Only used to classify building damage in a reasonable manner. Assist the Government and rescue teams for taking the best decisions.
Eligüzel (2021) [18]:Named entity recognition(NER) on tweets during earthquake by DL.	➢ NER was a text-based method of classifying and categorizing data from twitter.	Dataset: Earthquake twitter dataset. Performance: Precision - 0.94 Recall - 0.94	Distinction from the focused tweets might be caused by noisy outliers obtained from tweets.
Favour (2021) [19]:Predictive agent-based modeling (ABM) of natural disasters using machine learning.	➢ Agent based model (ABM) in natural phenomena (like wildfire, land suppression and hurricane) by using machine learning.	Dataset: Hurricane images from Atlantic region. Performance: Intensity accuracy - 73.7%, Longitude accuracy - 85.3%.	ABM was proposed with the help of Voronoi diagrams.
Sridhar et.al (2021) [20]: Real time fire detection and localization in video sequences using DL framework for smart building.	➢ YOLO v2 extract the electrical fire features more effectively.	Dataset: A total of 21,748 images were gathered from various fire databases. Performance: Duration - 0.4 seconds	Model had high probability of false alarms. Complicated algorithm, time-consuming, and ineffective hardware.
Asimakopoulou et.al (2021) [21]: Disaster management in smart cities	➢ A data-driven approach with artificial intelligence is being studied for limiting the effects.	Dataset: Gathered from sensors, remote device and unique identifiers.	Data integration and evaluation of predictions in real scenarios in order to perform data analytics.
Parimala et.al (2021)	➢ RASA classifies tweets	Dataset: Social	Model performed

[22]: Spatiotemporal-based sentiment analysis on tweets for risk assessment of event using DL approach.	and assigns a sentiment score based on the keywords provided by the network.	media tweets for disasters are collected. Performance: Accuracy - 86.4% Precision - 0.892 Recall - 0.894 F1-Score - 0.8912	well on English tweets and failed to identify other language tweet.
Munawar et.al (2021) [23]: UAVs in disaster management: application of integrated aerial imagery and CNN for flood detection.	➢ Drones and convolutional neural networks were used to quickly manage disasters.	Dataset: UAV based images collected from Sydney, Australia Performance: Accuracy - 91%	The sophisticated cameras in UAVs have a high-performance using image enhancement tools
Plata et.al (2021) [24]: Use of DL models in street-level images to classify one-story unreinforced MUR on roof diaphragms	➢ VGG19 was used for classifying one-story unreinforced MUR on roof diaphragms.	Dataset: 1122 images of MUR buildings Columbia. Performance metrics: Accuracy-0.80 Precision-0.88 Recall-0.84	VGG19 provides good accuracy precision and recall along with reducing number of resources.
Ekpezu et.al (2021) [25]: Using DL for acoustic event classification during natural disasters.	➢ CNN and LSTM networks were used for sound classifications.	Dataset: 2588 sound recordings were collected. Performance: Accuracy - 99.96% Misclassification rate - 0.4%	Acoustic signals were typically composed of a variety of sounds, including both disaster sound and noise.
Gude et.al (2020) [26]: Flood prediction and uncertainty estimation using DL.	DL used toforecast gauge height and assess the accompanying uncertainty.	Dataset: Flood images USA. Performance: RMSE - 3.5430 MAE - 2.7603	More accurate prediction with gauge height prediction at a smaller interval was achieved.
Iqbal et.al (2021) [27]: A process-driven and need-oriented framework for review of technological contributions to disaster management.	➢ A collaborative framework was developed in order to reduce the disaster effects.	Dataset: Landslide images at various locations in Australia	Lack of comprehensive benchmark datasets.
Sun et.al (2020) [28]: Applications of artificial intelligence for disaster Management.	➢ Uses AI tools to analyze disaster-related data for extensive damage and to mitigate its effects.	Dataset: Federal insurance and mitigation administration (FEMA) dataset.	Computational challenges.
Daud et.al (2020) [29]: Applications of drone in disaster management: A scoping review.	➢ Drone mapping was widely used to assess crop and human life damage in a various field.	Dataset: Disaster images collected by drone in disaster affected regions.	Finding and rescuing victims was tough for the DVI team.
Shen Chung et.al (2020) [30]: DL for post-hurricane aerial damage assessment of the buildings.	➢ Specific to region of Dorian Bahamas, where the video data was collected from two different locations. ➢ Video database was created with the help of CNN model. The dataset comprised of 5 UAV videos with 30 frames per second (FPS).	Dataset: A video database was created with 5 captured videos from unmanned vehicles with a frame rate of 30 FPS. Performance: 65.6% Accuracy	Few human annotators were used in this investigation, and huge, diverse tags were created.

3. Literature Review

3.1 Disaster Analysis Data Collection

The disaster dataset is collected inform images, audios, videos, and text by the help of artificial satellites, UAVs, mobile phones, and messages sent by social media etc. Few of the commonly used disaster assessment dataset by the researchers includes Hurricane Database2 (HURDAT2) for hurricane damage assessment, Open Street map dataset for Tsunami, Federal Emergency Management Agency (FEMA) for post disaster damage assessment, and precipitation data for flood prone areas assessment etc.

Various models such as LSTM, VGG16, VGG19 etc. are used in order to identify the severity of damages during the disaster. The details about the disaster database used by the researchers have been summarized in the Table 2.

Table 2: Disaster database

Dataset Collected	Description
Huricane database2 (HURDAT2) (Devaraj et.al., year, [1]) https://www.nhc.noaa.gov/data/	➢ Cyclone data collected from Atlantic and Pacific regions in 6-hours interval. ➢ Infrared satellite images in a CSV format have the information about location, highest winds, and central pressure information.
Federal emergency management agency (FEMA) damage dataset (Cheng et.al., year [6]) https://www.fema.gov/about/openfema/data-sets	➢ Collected from the Dorain region of the Bahamas. ➢ The dataset consists of 5 aerial videos at frame rate of 30 frames per second. Classifying the damage scale of disaster-affected buildings in UAV imagery.
Precipitation dataset (Kumar et.al., year [3])	➢ The precipitation data was gathered in Fiji's flood-prone areas in Fiji for identifying the devastation due to flood. ➢ Data was gathered in an interval of one-day, three-days, seven-days, and fourteen-days during the rainfall in India.
OpenStreetMap (OSM) dataset (Gupta et.al., year [7]) https://www.digitalglobe.com/ecosystem/open-data https://www.openstreetmap.org/	➢ Dataset was extracted from a 45-square-kilometer area around Palu city in Indonasia for the study of damaged roads ➢ The ground control points in the OSM pictures were roughly 50 cm pixel^{-1}.
Unreinforced masonry buildings (MUR) dataset (Plata et.al., (2021) [24]) https://github.com/Rise-group/masonry_diaphragm_prediction/tree/master/data	➢ Dataset was collected from Columbia by UAVs and consisted of 1122 images of unreinforced masonry buildings (MUR).
EM-DAT—The International Disasters Database [35]. https://www.emdat.be/guidelines	➢ In EM-DAT, natural catastrophes and technology disasters are the two basic categories of disasters. The disaster sub-group and the disaster category are automatically connected to this field.

4. Results and Discussion

This research article discusses about various disaster image classification techniques in case of hurricanes, floods, earthquakes, Tsunami, and landslide disasters. For the current work a total of 30 research articles were analyzed for identification of disasters in various regions. The datasets included image dataset, video database and social media data compraising of sentiment analysis tweets, sound recordings. The various DL models used for natural disaster management are VGG16, LeNet5, VGG19, SEResNxt-50, and SPDA etc. Few of the models failed to classify failed to classify the images for different situations like flood, cyclones, and wildfires and accuracy is less nearly 80%.

Few experiments were conducted on flood assessment where the xBD dataset compraising of satellite images having a resolution of 128 ×128. The dataset comprising of two groups of houses, each with 1000 images of completely and partially surrounded regions by flood water. Among these 700 images have been used for training, 100 images for validation, and 200 images from each class used to evaluate the trained model. The dataset has been obtained from the xView2 challenge [38]. Among CNN models which includes VGG16, custom CNN architecture and MobileNet architecture. Custom architecture gave an accuracy of 87.07% but all the other models suffered from overfitting which can be improved by increasing the number of images used for classification, performing various techniques such as data augmentation, rotation, scaling.

5. Conclusion

In this paper various post disaster management techniques are discussed along with their limitations. Here hurricanes, floods, earthquakes, Tsunami, and landslide disasters in different parts of world are discussed. Mainly researchers have used image processing, machine learning, and deep learning algorithms to assess the losses caused due to the disasters. In DL researchers have used CNN, DCNN, and transfer learning. As DL is very data hungry and database is small, researchers have used data augmentation and transfer learning before feeding the data into the network for training. Among the various models VGG16 and VGG19 performed well for post disaster damage analysis 99.96% [14].

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