Utilizing Deep Learning Technologies for Surveillance and Evaluation of Natural Anthropogenic Catastrophes: A Comprehensive Meta-Analysis

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Abstract. Disaster management is the managerial function of dealing with material, human, environmental, or economic impacts of disaster. It is the process to prepare, address, and learn from the impact of huge failures. Disasters can be caused by natural and manmade reasons. Disasters pose catastrophic and significant socioeconomic impacts along with human losses and economic failures. Recent advancements in the Deep Learning and the Machine Learning have been used to deal with catastrophic and severe effects of disasters. This study is focused on recent ML and DL approaches used in disaster monitoring and the assessment by various researchers and studies published since 2010 to present. Studies published in the areas of hazard assessment, catastrophe control, hazard prediction, calamity monitoring, and other measures have been focused. Furthermore, this study examines some of the most recently created ML and DL disaster management systems. This study also provides the future research directions to conclude findings.

Keywords: *Disaster monitoring, disaster management, deep learning, machine learning, artificial intelligence, natural disasters, manmade disasters*

1 Introduction

Natural or man-made disasters have a negative impact on the lives of millions of people around the world [9]. These catastrophic events are responsible for the loss of lives and livelihoods. Apart from human losses, disasters pose huge impact on properties and infrastructure. Hence, disaster management is very important before, during and after the incidents to prevent loss of human lives, protect infrastructure, and reduce the effects on economy and rebuild normalcy as quick as possible [10]. Complexity and criticality of disaster operations and complexity of disasters need proper decision making improved by artificial intelligence (AI) [10]. Some of the areas of application for ML and DL are earthquakes, hurricanes, floods, wildfire, and landslides. Recent technological advances can also help in managing artificial disasters like refugee crisis (Drakaki&Tzionas, 2021; Drakaki, Gören, &Tzionas, 2018). Disasters are also defined in different ways. A disaster is a critical hazard to the overall working of society which consists of significant losses and damages to mankind and infrastructure [14].

There are two categories of disasters – technological disasters and natural disasters [15]. However, manmade and natural disasters are the most common categories [16]. In 2020, climate-related disasters mainly caused 389 disasters which were recorded in the same year. The year 2020 was placed above the average when it comes to disasters recorded with 23% more floods and 26% more storms [9].

Background

Disaster management is the process of managing disasters over time in four different stages – mitigation, preparation, response, and recovery [10]. Mitigation is associated with activities which either prevent catastrophe or reduce the effects of calamity. Preparation consists of actions to help the societies to take action to deal with disaster like arranging supplies, planning for emergencies, education and training to respond to the disaster when it attacks or alleviate the shocks. Response cover operations to implement plans made to protect property and human lives, the community, and the environment [10]. Disaster control and retort also covers actions like making emergency plans, medical care, and emergency rescue,

distribution of supplies, opening and managing shelters, and damage assessment. Time is very important in this stage and high accuracy is very important to perform quickly. Recovery consists of longstanding actions to restore normalcy. This phase includes actions like rebuilding and financial assistance. Local communities should be actively involved in this process [14].There are several ML and DL models used as part of AI to help in disaster management in every stage. ML models include DT, SVM, NB, RF, K- NN, and LR. Meanwhile, DL methods consist of various architectures of artificial neural networks (ANN) like MLP, CNN, LSTM, RNNs, etc. [11,17, 18]. Various large and complex datasets have been used by ML and DL to develop systems to predict disasters and help in recovery and response after disasters. These techniques are able to operate various types of information from various bases and choose outlines to deliver intelligent support. Big data is also provided from sources like UAVs, satellite imagery, crowdsourcing, social media, WSN, and GIS.

2 Recent Works

As subfields of AI, ML and DL have played a vital role in a lot of areas to manage natural disasters in this age where natural disasters are constantly increasing due to manmade causes [1,2]. In this section, some of the recent studies have been analyzed in their application. Table 1 summarizes recent studies on machine learning and deep learning techniques, their accuracy, and their usage on different types of disaster

Table 1 – Recent Studies on ML and DL Techniques for Disaster Management

Disaster Managemen Approaches	Type of Disaster	ML/DL Techniques	Data collected	Accuracy and other metrics	Source
Disaster Mitigation	Flooding	KNN, BRT, NSC, and LB	Mapping flooding in 210 locations	Area under the Curve (AUC) = 92.74%	[3]
Disaster Mitigation/Assessment	Landslide	RF, Logistic Model Tree, NB Tree	Inventory map to collect data of 196 cases	Accuracy = 79.9%; AUC = 82.4%; Precision = 74.5%	[4]
Hazard and disaster prediction	Landslide	ANN, LR, SVM	HQ imagery data for remote sensing of landslide data	AUC = 0.881	[5]
Vulnerability and risk assessment	Hurricane	Deep Neural Network	Data from storm on Jan 2017 and Hurricane Hermine	Accuracy – 93.83%	[7]
Hazard and disaster	Earthquake	NN, RNN, RF	Data collected from	Accuracy =	[8]

prediction			Hindukush, Pakistan	65%	
Damage assessment	General	CNN, LSTM and VGG-19	Disaster data from Twitter "CrisisMMD" with over 18k images and 16k tweets	F1 Score = 85.7%	[9]

3 Research Questions

When it comes to hazard prediction and disaster monitoring, it is important to mitigate those risks and assess vulnerabilities by solving these research questions -

RQ1 - What are the recent advancements in DL and ML for damage assessment? RQ2 - What are the DL and ML approaches used in disaster monitoring?

4 Statement of the Problem

Considering the rising trend of evolution of ML approaches in the field of catastrophe control and rapid growth of deep learning, this study solves the problem of lack of studies on deep learning in disaster management by doing comparative study on machine learning and deep learning in disaster monitoring and damage assessment. This study covers various aspects related to disaster management with various techniques.

5 Objectives of the Study

Informed and robust catastrophic control is much needed to address the impact and scale of adversities leveraged by the advancements in ML and DL [11]. With that in mind, here are the objectives of this study

- To discuss DL and ML approaches used in disaster monitoring
- To discuss recent advancements in DL and ML for damage assessment

6 Importance of the Study

This study is significant for having complete insight to recent developments and ML and DL techniques used in catastrophe management and it will also help understand future trends in this aspect. It covers recent applications on DL and ML for disaster monitoring.

7 Scope and Limitation

When it comes to limitation, this study has not identified recent studies on AI models for long-term recovery from natural and manmade disasters. Disaster recovery is a huge term which covers different activities to bring civilizations back to normalcy, introduce efficient polices, and build resilience. This study opens further research path to cover these aspects.

8 Materials and Methods

Research Method

In order to fulfill the objectives of this study, Google Scholar was used to perform search for relevant articles published in journal databases, applying filters for articles published since 2010 to 2023. This search was performed using keywords like "natural disasters", "machine learning", "deep learning", "artificial intelligence", "manmade disasters", "disaster monitoring", "disaster management", etc. Initially, 1116 articles were found in initial search. With relevant experience, authors further conducted a search on top ranking journals of each database like Elsevier, IEEE, Springer, and others. They performed manual search to exclude irrelevant articles or studies which were out of scope. This way, 55 articles were finally selected for this study. Figure 1 illustrates the percentage of articles covered in this study from respective databases. Table 2 lists the group of keywords gathered to collect secondary data for this study.

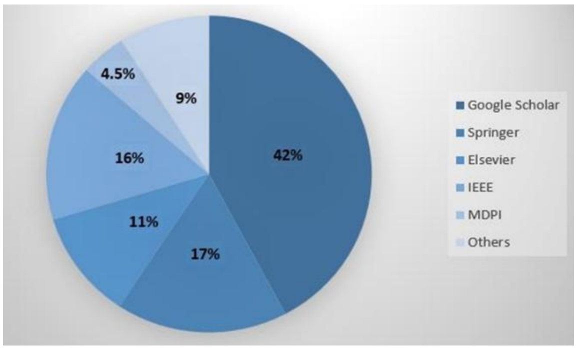

Figure 1 – Distribution of Publications by databases

Table 2 – Groups of Keywords Used for Data Collection

Group	Keywords
1	Machine Learning, Deep Learning, Artificial Intelligence
2	Disaster Management, Disaster Monitoring, Damage Assessment
3	Natural Disasters, Manmade Disasters
4	Deep Learning, Manmade Disasters, Natural Disasters
5	Machine Learning, Disaster Management, Disaster Monitoring

Inclusion and Exclusion Criteria

Inclusion criteria for this study includes –

- All the studies published in English language
- Studies with group of relevant keywords as mentioned in Table 2
- Studies which are relevant and published in databases as given in Figure 1
- All the studies which are published and available in full-length

Exclusion criteria for this study includes –

- Studies published in language other than English
- Studies with spelling and grammatical errors
- Studies which are irrelevant to the subject matter of this research
- All the other studies that don't fall under above criteria

9 Data Analysis

Machine Learning and Deep Learning Methods for Disaster Monitoring

Machine learning successfully removes irrelevant information and helps in faster analysis and processing of data on disasters and helps in all stages of disaster management successfully [18]. DL is a subclass of ML that can learn to represent a complex arrangement in order to detect, classify, and forecast. Deep learning relies on causal chains of the layers of NN that can provide more intellectual and accurate models [19,20].

Convolutional Neural Networks are best in computational roles, making aerial and satellite imagery platforms important for damage monitoring and responding to disasters [21]. ANNs are used significantly as an effective data analysis tool [22]. Meanwhile, text-based NNs such as LSTMs leverage their architecture to accomplish natural language processing tasks [23].

CNNs

The architecture of CNNs relies on “convolutional layers (CL)”. Theinformation is applied and propagated using tabulation multiplication of "n*m" filters or kernels, where n=m in most cases. Input data is represented in different ways by this process as per the filter applied. A lot of features are revealed in each representation projected in feature maps [19,20]. Figure 2 illustrates the architecture of CNN. It is worth mentioning that each convolutional layer offers the abstraction level in the process of feature extraction.

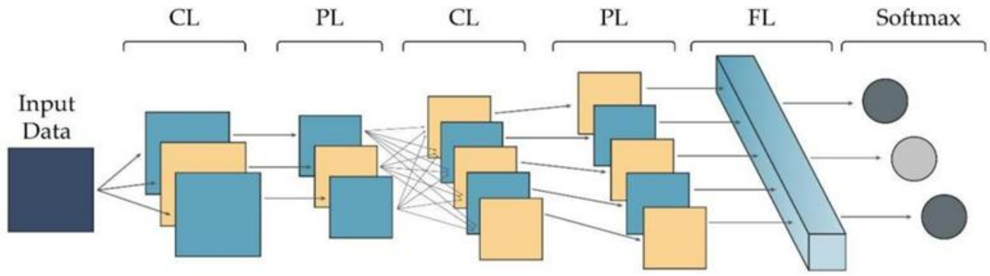

Figure 2 – A CNN architecture with pooling and convolutional layers along with a well-connected SoftMax layer

LSTM

LSTM is a widely used neural network used for text classification in datasets used in social media for disaster monitoring. These are "recurrent neural networks (RNNs)" that apply the same computation recurrently for each part of a sequence of sequential information while transferring some data to the next iteration. A prediction is made in each step on the input which ultimately influences the forecasts. This process enables system to comprehend multifaceted text-based information and extract meaning as per positional data of words. It is possible to tune the hyperparameters individually in LSTM that can save most of time during experimentation and training [24]. Figure 3 illustrates the diagram of LSTM architecture. The deep and exact breakdown of information is very important in several levels of disaster management and LSTMs are known to work effectively and efficiently.

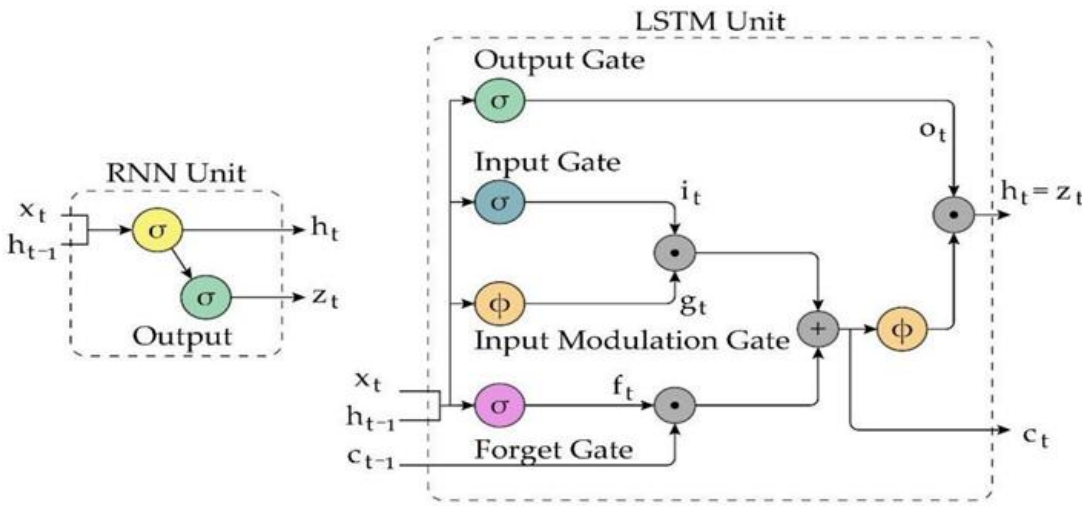

Figure 3 – An LSTM architecture [28]

SVM

It is one of the simplest and most effective machine learning models for tackling regression and classification problems. It is a model used for supervised learning which needs training set which is labeled already. Unlabeled data can also be categorized well with support vector clustering [24]. Though SVM works with vectors in linear fashion, non-linear classification can also be possible with kernel [25]. Live disaster monitoring and organization of data is very important for data scientists. Gopal et al. [26]

performed disaster monitoring using online news data. They used the approach of data scraping to crawl the data from various online sources and portals based on several hazard emergency alerts. As crawlers collected all the data but couldn't differentiate between useless and useful data, machine learning is used to pick only useful data by removing the useless data. This method could monitor online disaster news to help in disaster response and preparedness.

Domala et al. [27], used news data to improve emergency response by employing ML models and NLP. They used a scraping technique to fix the newscast from various sources, and then applied ML and NLP to such information to classify pertinent information, which was then shown and shared on emergency control websites.

Fan et al. [23] used hybrid machine learning techniques to discover disasters from social media posts in different countries for proper response to the disaster. Content from social media posts doesn't always have proper information which may affect the awareness of the situation and hide crucial details, according to studies conducted with geotagged location and coarse-grained event detection.

Machine Learning and Deep Learning Approaches for Assessment

Damage assessment covers different techniques which can scale the damage and estimate the resources required for disaster response. Wang et al. [8] showcased a DL-based multimodal algorithm for disaster assessment. CNN, LSTM and VGG-19 algorithms are used in this framework which significantly boosted the model's performance as it relied on automatic loss weighting method rather than process of tuning weight manually. The best part of this model was that it could easily detect the association among various concepts and data. The researchers used a large-scale dataset based on X to test and identify the impairment done by the disaster. This model can learn multiple tasks and outperform other individual models with 0.857 as F1 score.

Resch et al. [29] solved the problems of incomplete temporal and spatial vision as well as high number of lags. A novel ML model has been used to classify the hotspots by removing the semantic data and conducting spatial and temporal analysis on posts on social networking sites to analyze the impairment done by natural calamities. They identified natural disasters like earthquakes accurately and successfully in advance with various temporal and spatial properties. In addition, they created a loss map successfully by such disasters validated with "HAZUS loss model" [30]. The "US Geological Survey" was the official source for earthquake footprint for prediction and identification of earthquakes.

It is important to assess damage by natural disasters for timely relief and response. This way, Presa- Reyes & Chan [21] proposed a CNN model with "two-steamed network." The architecture proposed by these authors deals with the problems of current CNN applications, which organized the designs well between intact and destroyed and these programs still don't perform properly with over two levels of harm. The projected design deals with this challenge well and can classify at least 4 levels of damage with utmost accuracy. Researchers have captured the aerial pictures before and after hurricane and assessed the same with the given architecture. Concatenated features from those images helped very much in prediction as they could train the model. A publicly available dataset was used to determine this architecture.

Authors in [22] displayed a mix method and used machine learning techniques for classifying the flood-affected regions. Drone was used to click in-flight pictures of regions over different elevations as they can click HD pictures with different topographies. They used SVM and K-means clustering for the purpose of classification. Researchers have inserted aerial images to the structure which are then arranged as whether the region was affected by flood or not. Researchers have also used various kernel features in SVM to check system efficiency. It was possible to reduce the prediction and training time of the system by using quadratic SVM. Overall, 92% accuracy has been achieved with accurate classification of flood affected regions.

Yang & Cervone [31] proposed a combination of ML and DL for damage assessment as per the data collected from aerial images. Initially, critical infrastructure was identified using images with a pre- trained

CNN model. Then, several machine learning techniques like RF, SVM, KNN, RF, DT, and LR were used for capturing features related to affected regions. Then, researchers have developed max- voting ensemble classifier using the trained machine learning classifiers. They applied the proposed methodology for damage assessment of flooded regions in Texas with aerial pictures in 2015 and achieved 85.6% accuracy and 89.09% of F1 score.

Deep CNN has been used by Nguyen et al. [32] for natural disaster assessment. They found better performance in fine-tuned, domain-centric CNNs than other techniques. The fine-tuned model achieved

0.82 of F1 score and 0.84 accuracy for data received on earthquake in Nepal. Authors at [33] proposed a multi-modal, 2-stage scheme for damage classification. They trained the classifiers on semantic and visual features on the first stage. Semantic features relied on BoW and shape, texture, and color features were the part of visual features. Researchers used the outcome of first stage classification in second stage for training the new classifier. Twitter data was used for creating dataset. They achieved 92.43% of accuracy.

Authors at [34] proposed an approach based on deep learning for assessment of aftereffects of flood in rural and urban areas with satellite imagery. They assessed the impact of disaster using CNNs in urban areas with segmentation of topographical features like roads in images after and before disaster and identification of maximal change regions. A bitemporal image classification approach was developed for rural areas for disaster assessment while comparing the images before and after disaster. They tested the method for damage assessment in urban areas as per image from “DigitalGlobe” and impact of “Hurricane Harvey” was displayed with labeled data. They assessed damage for rural areas with images from 2017’s monsoon flooding in South Asia.

10 Results

Online video, text, and image data on social media has gained a lot of presence in disaster and crisis management. Proper decision making by decision makers and emergency responders can be promoted by data posted on Twitter and other social media platforms. Studies have been focused mainly on deep learning with Twitter data and social media. Studies have focused a lot on post-disaster response and analyzing and processing data from Twitter [35-39]. Twitter and other social media data have been used widely in disaster monitoring, disaster assessment, and detection.

Other sources of data used in various sub-stages consist of satellite pictures for vulnerability and assessing risk of damages as well as disaster discovery, record mapping for vulnerability, video for disaster detection, sensory output for hazard and disaster forecast, online news, and other image data from Google and AIDR platform for assessing damage. In addition, deep learning approaches performed better to reduce false data labeling and to assess damage in terms of black box nature [40]. Figure 4 illustrates the performance of deep learning and machine learning approaches developed in terms of correctness by type of tragedy. Highest precisions have been attained for response after catastrophe like flood, wildfires, hurricanes, and early warning signs like tsunamis and heavy rains.

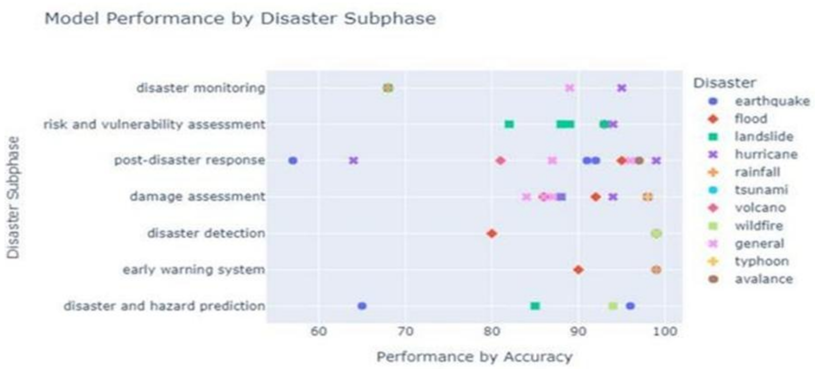

Figure 4 – Model Performance of Methods Developed with Accuracy by Type and sub-phase of disaster [28]

Figure 5 illustrates the performance of machine learning and deep learning approaches through varied accuracies achieved in various stages of disaster. A lot of studies have achieved 80 to 98 percent of accuracies in performance. Accuracy in disaster response peaks at 91%. It shows that most of the deep learning and machine learning models used for disaster management yielded 88.8% accuracy, irrespective of various stages. The correlation between data type and accuracy is another vital metric. Models which were based on image data performed slightly better in terms of accuracy. The average accuracy with image-centric models was 88.82% while the average accuracy of text-based model was 88.17%."

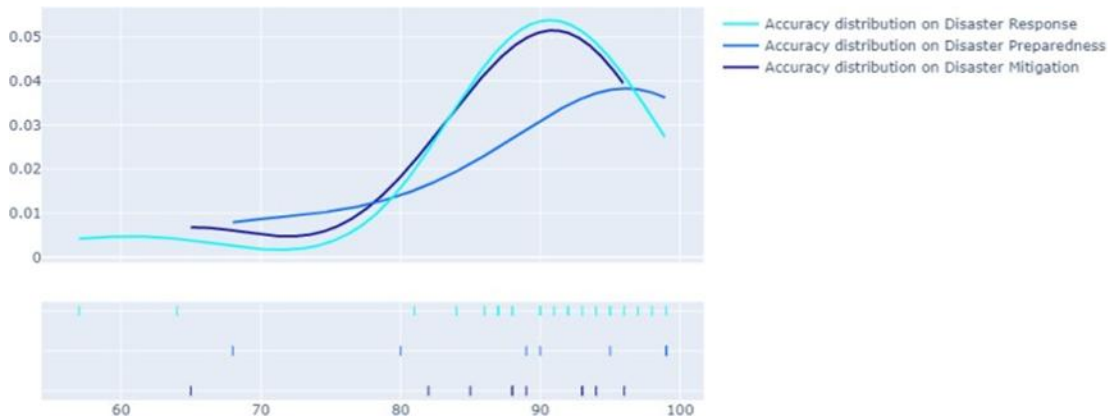

Figure 5–Performance of ML/DL methods developed as per accuracy for various stagesof disaster [28]

11 Conclusion

Natural catastrophes are among the leading causes of loss of human life, property, and infrastructure. Machine learning and deep learning techniques are commonly utilized in disaster management to deal with the complexities of natural and man-made disasters. This study examines machine learning and deep learning techniques in disaster management and assessment to improve their effectiveness. A lot of machine and deep learning techniques have been proposed for various disasters like lava flow, floods, typhoons, earthquakes, landslides, and hurricanes. There is a need to make operations related to disaster recovery sustainable while focusing on reducing vulnerabilities, mitigation efforts, and resilience.

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