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A Review on Disaster Prediction Using Machine Learning

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ABSTRACT

Climate changes are increasing, with it the natural disasters such as earthquakes, hurricanes forest fire, and floods occurrence rate are also on the rise. These devastating incidents result in human losses, significant impacts on infrastructure and properties and often catastrophic socioeconomic impacts. A lot of approaches have been taken to address issues related to natural disasters i.e. the development of early warning systems, risk assessment and management, disaster response and recovery, and the modelling of the natural disasters for the purposes of prediction and forecasting. The recent development in artificial intelligence (AI), deep learning (DL) and machine learning (ML) can help in better cope with the disaster prediction, detection, mapping, evacuation, and relief activities using sources of big data such as satellite imagery, social media, and geographical information systems (GIS). This paper aims to review research studies that utilize big and complex datasets to develop ML system that can predict and assist before, during and after disasters. Finally, the paper discusses the limitations and future directions of using machine learning for disaster prediction, classification, and highlights the need for further research in this area. Overall, this paper provides a comprehensive overview of the current state of the art in using machine learning for disaster prediction, classification and identifies opportunities for future research.

Keywords: Machine learning, Disaster prediction, Classification. Artificial Intelligence

INTRODUCTION

The world has witnessed a breaking number of disasters in the last few years with a record of more than 300 natural disaster in the second half of 2020 and the first of 2021. This outpaces the recorded numbers from 2000-2019 with average of 185 disaster(Sreelakshmi and Vinod Chandra 2022). A number of 389 climate-related disasters only were recorded during 2020. As a result, the number of recorded disasters during the same year was greater than the average of the statistically recorder number in the previous years with 26% more storms and 23% more floods combined with a higher number of human and economic losses (Linardos et al. 2022a). These calamitous incidents significantly affect the infrastructure and properties resulting in homeless people, impacts the public mental health of the survivors who have lost everything due to this unforeseen and unpredicted natural hazard in the affected area and consequently causes socioeconomical losses.

Disaster prediction and detection contributes to reducing the number of casualties and the economic losses. Properties and natural resources can be protected in some cases such as hurricanes and floods if early warning systems are provided (Gupta and Kumar Rana n.d.). However, even with a short period of notice before disaster, people can take actions to protect themselves against harm and death. Therefore, vast investment needs to be done by governments to enhance the disaster detection and management systems using the recent technologies made by the advances in computer science that eased the access to large amount of data (Chamola et al. n.d.).

There are several data sources that can be obtained and combined to provide insights on the current situation and assist in decision making. Such data can be gathered from social media, satellite imagery and geographical information systems (GIS). Although, the usefulness of this large volume of data, it is challenging to the decision-makers to analyze it with the absence of the right tools (Kaur et al. 2022). Therefore, the urgency to utilize advanced algorithms such as Machine Learning (ML) and Deep learning (DL) is up raising. As a branch of artificial intelligence (AI), ML employs algorithms that draw on the properties of existing data to generate new predictions. It has the ability to process large amount of data quickly and discover patterns. Furthermore, as the amount of data increases alongside with its diversity, ML algorithms often perform better. For instance, the capacity of the algorithm to forecast rises as the amount of data increases in an earthquake prediction model (Chamola et al. n.d.). Further, the subfield of machine learning, DL, is capable of autonomously learning the representation of a convoluted system for classification, prediction, or detection. DL employs extensive causal chains of neural network (NN) layers allowing for more advanced and abstract computational representations of the real system (Lecun, Bengio, and Hinton 2015) (Schmidhuber 2015). In order to learn invariant characteristics and extremely complicated functions, DL approaches enable representations with multiple degrees of abstraction, achieved via simple, non-linear modules that change the representation to a higher, more abstract one at each level (Lecun et al. 2015). Thus, the advancement of DL in problem solving has allowed it to be part of many solutions developed for critical issue like disasters.

The use of ML algorithms minimizes human intervention which by extension minimizes the human errors that might occur while dealing with a large number of complex data. As they are being trained by utilizing such amount of data to discover patterns and hand out predictions (Linardos et al. 2022b). Those predictions will be used in the preparation for the disaster; besides they will help in decision making at the time of the disaster and after it. Considering that quick efforts must be done to prioritize rescue operations and provide aid to the affected individuals, in reaction to this catastrophic event (Doshi, Basu, and Pang 2018). This paper reviews the available applications of ML in disaster prediction and control, covering the process of per-disaster management, crowd assistance and evacuation, post-disaster management.

A. Disaster Prediction Techniques

The research community has been focusing significantly on utilizing the AI methods in disaster prediction models in the recent years. Generally, prediction methods can be classified into two categories mainly: traditional method and artificial intelligence method.

B. Traditional method early versions of artificial intelligence methods

C. Experience-Based Analysis

By mimicking the human memory in remembering the past problems and the using of the accumulated experiences to solve the new ones, Case-Based Reasoning (CBR) model was proposed (López De Mántaras et al. n.d.). The CBR mechanism is used to identify the similar properties between a previously solved problem and a new problem, then it applies the successful solutions of the past problem on the new one (Zhu, Zhang, and Sun 2019). However, this mechanism may not always propose suitable solutions to the current problems. As the data retrieved from the previous problems usually contain inaccurate or missing data due to the abruptness of the urgency or the solution is not compatible with the current problem (Shimin, Huizhang, and Liu n.d.). To overcome this shortage the CBR model was integrated with Role-Base Reasoning (RBR). RBR considers the decision-makers requirements by applying “IF THEN” rules to the solutions obtained by the CBR. So that the decision-makers can adjust the solutions to suit the current situation. Additionally, techniques such as risk analysis and fuzzy theory was combined with CBR, in order to enhance the search efficiency and tackle the uncertainty of the information (Huang, Wang, and Liu 2021).

D. Time Series Analysis

Time series analysis was designed to drive significant statistical measurements and to identify patterns within a time series. It then uses these data to estimate the future values for the same time series. However, it was found out that the data collected during disasters and emergency events were non-stationary (Zhu et al. 2019). Several approaches are used to enhance the time series forecasting in prediction such as the autoregressive integrated moving average (ARIMA) and seasonal autoregressive integrated moving average (SARIMA) (Athiyarath, Paul, and Krishnaswamy 2020). ARIMA model encompasses three parameters that should be driven from the available data known as (p,d,q). Each parameter represents a part of the ARIMA model, autoregression (AR) which determine the number of the autoregressive terms using the parameter p, integrated (I) calculates the degree of differencing with the parameter d and moving average (MA) that represents the number of the moving average terms by the parameter q (Hipel and McLeod 1994). The seasonal ARIMA known as SARIMA is $(p,d,q) \times (P,D,Q)$ divided into (p,d,q) the nonseasonal autoregressive moving average and (P,D,Q) the seasonal autoregressive moving average (Vagropoulos et al. 2016).

E. Fuzzy Theory-Based Method

During disasters and emergency events, decision making process is surrounded by uncertainty and ambiguity. The reason for that is the imprecise and limited nature of the available data information. The characteristics of the available data make the decision making process in such events hard and unreliable (Sun, Ma, and Zhao 2013). Fuzzy set theory has presented a robust method to address the imprecise parameters using a quantitative representation and manipulation of the imprecision in the decision-making problems (Ba¸sar et al. n.d.). Fuzzy set methodology gained increased effectiveness by labelling the imprecise parameters as imprecise rather than treating them as precise (Kahraman, Gülbay, and Kabak n.d.). Which led to enhancement of the creditability of the methodology results.

F. Bayesian Network

The Bayesian network approach is a probabilistic representation of a graphical, mathematical model the illustrates the conditional dependencies among influencing factors and predict the progression and impact of emergency events. This enables a comprehensive monitoring of the evolving dynamics of the disaster's impact in real-time (Gerber Machado, de Oliveira Ribeiro, and Oller do Nascimento 2023). The model consist of a) a directed acyclic graph that defines the conditional dependencies between the variables, b) the strength of the dependencies as quantified by the conditional probabilities (Kaikkonen et al. 2021).

G. Machine Learning Modern Versions Of Artificial Intelligence

Machine learning main concern is to find patterns and determine the characteristics in the given data using its algorithms and methods to provide predictions without direct programming (Zagorecki, Johnson, and Ristvej 2013). Since its introduction in the field of disaster management, machine learning has developed into one of the most efficient techniques for removing irrelevant data and accelerating analysis in disaster scenarios, which aids in rapid prediction analysis and selecting the ideal response tactics. It has a high level of accuracy in data classification and pattern detection in comparation with the old methods, due to its ability to adapt with the issues and learn from it without depending on statistical hypotheses about the distribution of data (Yu, Yang, and Li 2018).

ML uses different algorithms or approaches to understand data. These algorithms can be divided to supervised learning, unsupervised learning, and reinforcement learning.

H. Supervised Learning

In supervised learning the machine figures out the pattern of the data and classify it by comparing the inputs to the outputs using labelled examples (training datasets). After learning the patterns, the machine ability for prediction and classification is tested using unlabelled examples (testing dataset) (Mahesh 2018). Supervised learning has two major techniques, classification, and regression. Classification technique categorize data into pre-set classes in order to predict the likelihood that a data item belongs to a certain group. While regression associates a data object with a meaningful predictive variable.

I. Unsupervised Learning

On another hand, unsupervised learning is required to find meaning full patterns in unlabelled data that has no correct answer by clustering them (Chamola et al. n.d.).

J. Reinforcement Learning

Lastly, in reinforcement learning the machine gets rewards or punishments depending on how it behaves in the given environment. The main goal of the reinforcement learning technique is to maximize the rewards (Mahesh 2018). The management of pandemics and disasters may be carried out in a variety of phases using all of the above ML algorithms.

K. Machine Learning Application In Disaster Management

Machine learning algorithms' ability to utilize multidimensional data is highly beneficial in disaster management. As disaster management aims to reduce the total loss of lives, properties and infrastructure, ML models were used in various stages of disaster management such as disaster prediction, crowd evacuation and post-disaster scenarios. This section will discuss in detail the above-mentioned stages of disaster management.

L. Disaster Prediction

In disaster prediction, regional and geographical data need to be analysed accurately to identify the attributes of a disaster, such as a flood's water level, the magnitude of an earthquake, or the slope stability of the landslide in order to minimize the unpredictability of the catastrophic events. Yuan and Moayedi introduced an optimization of the multilayer perceptron (MLP) classification technique to predict the landslide. They obtained the highest classification accuracy with the percentage of 85% of landslide predictability. There technique used MLP NN with six other methods, ant colony optimization, biogeography-based optimization, evolutionary strategy, genetic algorithm (GA), probability-based incremental learning and particle swarm optimization (Yuan and Moayedi 2020). Hafiz et al. accelerated the training of the SVMs for flood detection with an accuracy of 90% and shorter processing time. They applied image processing to improve the classification results of the input images (Munawar, Hammad, and Waller 2021). Khalaf et al. designed a flood detection system using sensor network to detect the water level that sends notification via SMS and web base public network through GSM modem. They analysed the obtained data using machine learning algorithm to determine the likelihood of flood occurrence. They used four different algorithms to classify the flood data namely Random Forest algorithm, Bagging algorithm, Decision Tree algorithm, and HyperPipes algorithm. Only Random Forest algorithm got the highest classification accuracy with 99.5% accuracy (Khalaf et al. 2015).

M. Crowd Evacuation

Natural disasters have always caused suffering to countless individuals worldwide. The delay in evacuating during such events frequently results in a higher number of casualties. Identifying the disaster locations in constrained timeframe is essential to have more rapid evacuation. However, it is a highly critical and challenging task. Researchers have developed many approaches, but they have lacked capabilities to assist immediate evacuation following the occurrence of the disaster. Xialong Xu et al. suggested a new algorithm in a mobile cloud computing framework based on IoT to developbn an evacuation planning system for densely populated areas during disaster situations. They also employed the artificial potential field to compute the threshold distance to the shelter, thereby guiding the direction of the evacuation (Xu et al. 2018). Rossnagel et al. introduced a mobile communication-based alarm device like a global system, but the system showed failure for rapid evacuation (Rossnagel and Scherner n.d.). Anzengruber et al. developed a Smartphone application that evaluates the position of the user and closeness relations (Jatowt et al. 2013). Torii et al. (Torii et al. 2010) developed a model to assist fishermen with tsunami warning and evacuation. This is almost similar to the GPS connected to mobile phone devices.

N. Post Disaster

Rehabilitation measures and recovery plans from disasters need detection for post-disaster changes and evaluation for the economic losses. Many of the previously documented techniques have failed in analyzing changes and performing calculations due to insufficient data. Ren et al. introduced a machine learning-driven model designed to gather UAV data, which is then fed to an SVM classifier to Identify potential threats in the region. Once any threat is detected, the SVM triggers a signal to the UAV (Brighente et al. 2019). A.Cooner et al. conducted an in-depth study evaluating the efficiency of various Machine Learning algorithms, including multilayer feed-forward neural networks, radial basis neural networks, and Random Forests in detecting the damage of earthquakes. Moreover, they reported that these methods achieved accuracy levels exceeding 90% (Cooner, Shao, and Campbell 2016). F. Alidoost et al. introduced a new deep model for Identifying damaged areas (Arefi and Behr 2018). HS Munawar et al. Proposed an innovative machine learning approach using image processing the detection of flood-affected regions. Their model has shown enhanced accuracy and less training time compare to previously used methods (Suliman Munawar et al. n.d.).

O. Data Sources

The amount of data that can be utilized in crisis events prediction and management is qualified to be called Big Data as it can fulfil the characteristics of the Big Data in terms of data volume, data variety, data velocity and data value (Goswami et al. 2018). Which allows the researchers to extract valuable information through efficient analysis to an extensive amount of data (Yu et al. 2018). Some of the major big data sources that are increasingly used in disaster management are Hydrological data, Geological data, Remote sensing data, Google information system (GIS), Crowed source data, etc. Most of the mentioned data are either free or open source however there are some paid sources (Goswami et al. 2018).

P. Social Media and Crowd Sourced Data

Social media has become an essential part of our daily life. it is the fastest communication tool for news spreading, fund raising, and gathering volunteers through various platforms such as Facebook, Twitter, Instagram, YouTube, etc, as they contain millions of active users (Namrata Topno n.d.). The disaster news spread almost immediately after the disaster occurrence allowing organisations and volunteers to act fast as it was the case for Haiti earthquake in January 2010. The propagation of the news on social media resulted in US$8 million donations for the Red Cross in only 48 hours (Gao, Barbier, and Goolsby 2010). The northern region of Italy got struck by a devastating earthquake on 29th May 2012, the information and details about the earthquake and the situation of the affected areas and people were available on internet within 50 minutes from the crowed sourced data (Alexander 2014).

Q. Satellite Imagery

Over the past two decades, the usage of the observational images of earth obtained from satellites is increasing due to their ability of assessing the disaster situations (Voigt et al. 2016). Satellites provide large number of images with high resolution that is utilized in changes detection related to changes in the structure of land areas, alterations in direction, creation of water bodies, and information about the condition of damaged buildings in the disaster-affected region (Yu et al. 2018). Despite challenges faced due to the delay in the collection and analysis of satellite imagery, impacting the promptness of information dissemination by disaster management systems following a disaster occurrence (Havas et al. 2017). The integration of satellite imagery with advanced technologies like CNNs that is trained using pre- and post-disaster imagery for efficient post-disaster damage detection (Tilon et al. 2020), and time series when it is used in satellite imagery analysis (Van Etten et al. 2021). The multiplicity in the integration methods demonstrates its potential for enhancing disaster response and risk management.

R. Weather and Climate Data

One of the essential data sources for weather-related disaster prediction and monitoring is meteorological data, including information from weather stations, radars, and climate models. Meteorological data provides essential information on atmospheric conditions, such as temperature, humidity, wind speed, and precipitation, which are fundamental for understanding and forecasting weather patterns and extreme events (Ianevski et al. 2019). Utilizing meteorological data with machine learning methodologies, the disaster prediction, risk assessment, and management show promising improvement. Honag et al., used daily rainfall and temperature data in an early warning data that was developed to prevent flood in mountainous area (Van Hoang et al. 2019).

S. Sensor Networks

A study made by (Al-Fuqaha et al. 2015) highlighted the growing importance of IoT applications deployment in various aspects of our life, emphasizing its role in disaster management. Wireless Sensor Network has the ability to reduce the energy consumption while integrating data fusion from diverse sensors through reliable data transmission (Yu et al. 2018). WSN and IoT technologies has been instrumental in natural hazards monitoring. According to (Adeel et al. 2019) a number of studies has focused on landslide observation using WSN.

Ref.	**Year**	**Disaster Type**	**Dataset**	**Technique**	**Performance matrix**
(Yuan and Moayedi 2020)	2020	Landslide	Geospatial data including 15 independent variables and a binary landslide occurrence index	Conventional machine learning techniques and advanced metaheuristic evolutionary algorithms	prediction accuracy 87.8–98.3% classification ratio 60.1–85.0%
(Gude, Corns, and Long 2020)	2020	Flood	Hourly recorded data for the gauge height data from 15 May 2016 5PM to 1September 2019 4PM	ARIMA, LSTM	ARIMA RMSE: 2.0813, MAE: 1.9442 LSTM RMSE: 1.9558, MAE: 1.7010
(Khalaf et al. 2015)	2015	Flood	Flood data collected from the environment agency website in the United Kingdom over a five-year period, consisting of 1000 records with attributes such as weather, tides, season, months, and flood depth measurements	Random Forest, Bagging, Decision Tree, HyperPipes	Random Forest 99.5%, Bagging 97.7%, Decision Tree 94.6%, HyperPipes 89.8%.
(Nsengiyumva and Valentino 2020)	2020	Landslide	Inventory map contained 196 past landslides	Logistic Model Tree (LMT),	Naïve-Bayes Tree:

				Random Forest (RF), and Naïve-Bayes Tree (NBT)	Accuracy = 0.799 Precision = 0.745 RMSE = 0.301 Random Forest: Accuracy = 0.733 Precision = 0.692 RMSE = 0.428 Logistic Model Tree: Accuracy = 0.762 Precision = 0.724 RMSE = 0.364
(Shahabi et al. 2020)	2020	Flood	Sentinel-1 images, Remote sensing data, Field surveys	KNN, Bagging tree	Cubic-KNN MSE = 0.0396 RMSE = 0.1989
(Zhou et al. 2018)	2018	Landslide	High-resolution remote sensing imagery data of Pleiades-1 (9/22/2014) and GF-1 (3/30/2015) and historical landslide data, Longju in the Three Gorges Reservoir area in China.	SVM, ANN, LR	SVM: AUC = 0.881 ANN: AUC = 0.836 LR: AUC = 0.697
(Dodangeh et al. 2020)	2020	Flood	Flood inventory map, Geospatial database	Bootstrapping (BT) Random subsampling (RS)	RS-GAM: AUC = 0.95 RS-MARS: AUC = 0.96 RS-BRT: AUC = 0.92 BT-GAM: AUC = 0.98

					BT-MARS: AUC = 0.97 BT-BRT: AUC = 0.95
(Asim et al. 2017)	2017	Earthquake	Earthquake data from the Hindukush region, Pakistan.	Pattern Flood vulnerability assessment intensity map recognition NN, RNN, NN, RF, linear programming boost ensemble	LPBoost ensemble: Accuracy = 65% RNN: Accuracy = 64% Random forest: Accuracy = 62 % PRNN: Accuracy = 58 %
(Tanim et al. 2022)	2022	Flood	1000 random samples, including 800 ‘non-water’ and 200 ‘water’ pixels.	Support Vector Machine SVM, Maximum Likelihood Classification MLC, Random Forest RF, Unsupervised classification	SVM: Accuracy = 87% CD: Accuracy = 87% MLC: Accuracy =83% RF: Accuracy =69%
(Hashi et al. 2021)	2021	Flood	Observations of the river water level using a sensor	Random Forest, Naive Bayes, J48, CNN	RF: Accuracy = 98.7 % NB: Accuracy = 88.4% J48: Accuracy = 84.2% CNN: Accuracy = 87%
(Muhammad, Ahmad, and Baik 2018)	2018	Fire	Images and videos from various fire datasets	CNN	Accuracy = 94.39%, F1 score = 89%
(Sankaranarayanan et al. 2020)	2020	Flood	Observation of rainfall and flood	SVM, Naïve Bayes, KNN, DNN	DNN: Accuracy = 91.18%

			occurrence in two states in India Bihar and Orissa from 1990 to 2002		KNN: Accuracy = 85.73% SVM: Accuracy = 85.57% Naïve Bayes: Accuracy = 87.01%

TABLE I. TECHNICAL ANALYSIS OF THE ML/DL BASED ON PREVIOUS RESEARCH STUDIE

CONCLUSION

Natural disasters have frequently and widely damaged many lives in the last few years. The advancement of machine intelligence has profoundly impacted disaster and crisis management. This paper critically reviewed the applications of Machine Learning methods in disaster management in all stages. Building hybrid Machine Learning models: This study shows that we need to combine different approaches for better management of disasters and proactive decisions. Dealing with an area such as disaster management where multimodal data needs to be processed, we need machine learning models that can learn patterns and insights from different data modalities such as crowed sourced, satellite images, and meteorological data. Building such hybrid systems would be another interesting research dimension worth exploring in technology-enabled disaster management. The practical results are not evident to cope with real life applications, which stress the importance of hybrid models for better analysis and interpretation.

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