International Journal of Industrial Engineering
2023;7(2):57-64.
ISSN: 2456-8449

Natural Disaster Prediction with Cloud Integration for Enhancing Validation Using Gradient Boosting Algorithm

Srikanth MS[1*], Vivek.Sharma S[2], Raghavendra Vijay Patil[3], Sagar Ramesh Pujar[3]

[1]*School of Computer Science and Engineering, REVA University, Bangalore, Karnataka, India.*
[2]*Department of Computer Science and Engineering, Nagarjuna College of Engineering and Technology, Bangalore, Karnataka, India.*
[3]*Department of Computer Science and Engineering, KLS Gogte Institute of Technology, Belagavi, Karnataka, India*

[*]*Corresponding author: sivakumar.t@kpriet.ac.in*

Abstract. Annually, natural catastrophes inflict heavy tolls in terms of human lives lost, property destroyed, and economies hit hard. Information and communications technology (ICT) enables the executions of diverse models that handle different parts of disaster management, while geospatial scientists work to reduce or control these risks via computer modelling of these complicated occurrences. Complex natural hazard models, requiring large-scale computing resources, intense data, and concurrent access, make it impossible to execute these models using standard ICT foundations in a timely way. Offering natural hazard modelling systems as end service is now more feasible than ever before, because cloud computing's almost infinite computing, storage, and networking power, which can handle these issues. Researchers still have a way to go before they can fully embrace and put Cloud Computing technology to use in disaster response. Therefore, this paper compiles all these difficulties, discusses recent trends in the field, and lays out a theoretical framework for a Cloud-based solution that makes use of the Gradient Boosting algorithm to improve the validation of systems for modelling and managing natural hazards. These systems would make use of Cloud infrastructures in tandem with other technologies, such as IoT network, fog, and edge computing. Result shows that 90% of accuracy and less prediction time compared to training time of the dataset.

Keywords: Natural Hazard, Cloud Computing, Geospatial Science, Disaster Management and Gradient Boosting Algorithm

INTRODUCTION

The many opportunities presented by big data in terms of visualizing, analyzing, and forecasting natural catastrophes have unquestionably expanded the scope of natural disaster management in the modern era. From these vantage points, big data has significantly altered how human civilizations enhance methods for managing natural disasters to lessen the impact on individuals and the economy. Making the most of big data, gathering information from various sources and storing it in a way that could be effectively utilized during various stages of disaster management has become the primary goal of computer experts and policymakers in today's information-dependent world [1]. The purpose of this research was to analyses the literature systematically on the topic of big data's impact on disaster management and to highlight where the field is in terms of technology's ability to address these issues. This article summarizes the results of many studies that take a variety of scientific and technical stances on the topic of big data's potential to aid in disaster management. The purpose of this paper is to provide a comprehensive overview of the main big data sources, their contributions to various stages of disaster management, and the emerging technological topics related to using these new ecosystems of Big Data for monitoring and detecting natural hazard, mitigating their effects, aiding relief efforts, and taking part in recovery and reconstructions [2].

Natural calamities such as floods wreak havoc every year, destroying crops, homes, and other man-made structures. Many hydrological and climatic conditions might cause flooding. Catastrophe management and food prediction systems have both seen a lot of study. Nevertheless, with the aid of new technologies, it is now crucial to move away from individuals monitoring and predictions frameworks and towards smart flood predictions systems that include stakeholders, and the flood impacted people equally. Combining embedded systems hardware with a wireless communications network, the Internet of Things (IoT) allows for the real-time transmission of

Received: 08.08.2023 Revised: 24.09.2023 Accepted: 08.10.2023

sensed data to computer devices for analysis [3].

Mathematical and hydrological models have given way to algorithmic techniques in flood prediction research. The data pertaining to floods is non-linear and constantly changing. Flood prediction systems are developed using methods like artificial neural networks. With the purpose of developing the scalability and dependability of flood control systems, this study develops an IoT based flood monitoring, and an artificial neural network (ANNs) based flood predictions. To analyses historical data for flood predictions, this system primarily tracks environmental variables such as humidity, temperatures, pressures, rainfalls, and river water levels. Data analysis in flood predictions makes use of an ANN methodology, while the IoT method gathers information from sensors and facilitates connection over Wi-Fi. To enhance earthquake risk assessment (ERA), this study introduces a new method that combines fourfold artificial neural network cross-validations (ANN-CVs) with a hybrid analytics hierarchy process-method for Order of Preferences by Similarity to Ideal Solutions (AHP-TOPSIS). The model is then tested in Aceh, Indonesia. New research suggests that neural networks may enhance city-scale probability mapping. In earthquake-based probability research, the network architecture design with probability index has not been investigated. The purpose of this research was to identify the most important metrics for probability mapping prediction accuracy and to provide a framework for their improvement. Before moving on to the next phase, which was to analyses potential dangers, probability mapping was performed. Second, considering both structural and social aspects, a vulnerability map was constructed [4].

Lastly, the ERA was computed by multiplying the hazard and vulnerability indices. The population and regions at risk were then determined. With a consistency ratio of just 0.06, the results reveal that the suggested model is 85.4% accurate. Approximately 23% of the city's total area (14.82 km2) and 54,695 people live in an area where the risk level ranges from very high to high. Input parameter selection affects the model's performance, which in turn influences the choice of input layers and the network design. Outperforming both conventional and some preexisting probabilistic models, the suggested model outperforms both in terms of generalizability. Because the input parameters may be localized, the suggested model could be easily applied to different places, making it a simple and transferable tool for planning to mitigate and minimize earthquake risk [5]. Experts in disaster risk reduction have come to recognize, particularly in the wake of the 2004 tsunami and earthquake in the Indian Oceans, the significance of local knowledge and practice in lowering risks and enhancing disasters preparation. But communities, researchers, practitioners, and policymakers have not yet routinely used them. In our view, catastrophe risk reductions and climate changes policies, education, and activities must first include local and indigenous knowledge with scientific understanding. Using data collected from a study that included coastal and small island communities in Indonesia, the Philippines, and Timor-Leste, this article lays out a method for combining scientific understanding with local and indigenous knowledges on hydro-meteorological dangers and climate changes [6].

The method begins with gathering local and indigenous knowledge via observation, recording, validation, and classification. From there, it may be chosen to be integrated with scientific information. What makes this method special is that it gives communities the chance to do two things: (1) find information that can be incorporated into science and shared with researchers, practitioners, and policymakers; and (2) protect and value knowledge that cannot be explained scientifically. Want to encourage the uses of indigenous and local knowledge to help communities become more resilient to the effects of climate change and natural catastrophes by presenting a strategy that can be applied in other nations [7]. The problem statement is discussed below. Severe risks to life and property are posed by natural catastrophes such as hurricanes, earthquakes, floods, and wildfires. To respond and mitigate these calamities in a timely manner, early prediction and correct validation are of the utmost importance. Scalability, integration of real-time data, and validation accuracy are three areas where current prediction systems are challenged. The massive amounts of data produced by many sources, such as seismic sensors, weather stations, and satellite photography, are too much for traditional prediction algorithms to manage. To enhance the accuracy of predictions, a scalable system is required that can quickly handle and analyses massive information.

Prediction models are often not updated with the most recent information since many current systems do not have the capability to integrate data in real-time. To provide accurate predictions in response to changing environmental circumstances, the model must be able to integrate data in real-time. The accuracy and generalizability of models used to forecast natural disasters depend on their validation. Model performance could be subpar since existing validation procedures don't account for all the nuances of real-world circumstances. Modern validation methods are required, and cloud-based resources may be used to improve validation procedures. Scalability and cost-effective data processing may be hindered by traditional prediction models' inefficiency in using cloud resources. An effective and long-lasting prediction system can only be achieved by making optimal use of cloud services' resources. In the event of a natural catastrophe, prompt evacuation and reaction depend on clear and concise communication. It is possible that the public and appropriate authorities are not receiving timely and correct information due to the limitations of current warning systems.

The following are the contributions. Help find, gather, and combine weather, seismic, and environmental information that pertain to natural catastrophes. Putting systems in place to integrate data in real-time so that the prediction model is updated all the time. Helped clean and prepare the data for analysis by removing errors, outliers, and missing numbers. Participation in feature engineering to improve the model's prediction capabilities via the extraction of relevant features. Helped choose and deploy Gradient Boosting Algorithms (e.g., XGBoost, LightGBM) for hazard prediction based on natural phenomena. improving the algorithm's performance by adjusting its hyperparameters. Active participation in the system's cloud infrastructure architecture, including choosing cloud platforms and services (e.g., EC2, S3, Lambda) from Amazon Web Service (AWS), Microsoft Azure, or Google Cloud. The efficiency, dependability, and scalability of the cloud are guaranteed. The part in preparing the prediction model for use with past data. Contribution to validation efforts, with a focus on improving model accuracy and resilience via the use of cutting-edge methods. Working together on cross-validation techniques to guarantee the model performs adequately when exposed to new data. Work on real-time data processing pipelines using technologies like Google Cloud Pub/Sub, Apache Kafka, and Amazon Kinesis. Assuring that the prediction model is regularly updated with fresh data to adjust to changing environmental circumstances. The creation of an intuitive interface that allows users to easily see the model's predictions and insights. Facilitating access for those with and without specialized knowledge. Help establish a mechanism to notify the public and appropriate authorities about impending natural disasters. Streamlined alert dissemination by integration with cloud-based messaging systems. Assisted in establishing systems for tracking the model's performance and its evolution.

Contribution to routine model upgrades and maintenance with the purpose of improving forecast accuracy and making the model more resilient to new data. Section 2 will include the subsequent literature review, and Section 3 will discuss natural catastrophe prediction with cloud integration, specifically using the proposed gradient boosting technique. The results and comments on the supplied dataset are then addressed in Section 4, with the aim of enhancing the validation. The last section discusses the system's overall performance and future goals for natural catastrophe prediction.

LITERATURE SURVEY

Natural catastrophes, of which floods are a kind, are notoriously difficult to predict and prepare for. Risk reduction, policy recommendation, reduced property damage, and minimized human life loss were all outcomes of research into improving flood prediction models. Over the last 20 years, machine learning (ML) techniques have made significant strides in improving prediction systems, delivering more efficient and cost-effective solutions, by simulating the intricate mathematical representations of physical flood processes. The immense potential and several advantages of ML caused it to gain immense popularity among hydrologists [8]. The goal of researchers is to find better prediction models by combining current ML approaches with new ones and introducing newer ML methods. This paper's key contribution is that it showcases the present status of ML models for flood predictions and provides insights into the best models to use. To provide a comprehensive overview of the several ML algorithms employed in the area, this study specifically investigates the literature that has benchmarked ML models via a qualitative review of robustness, accuracy, and speed. An in-depth grasp of the various methods is provided by comparing the performance of ML models within the context of a thorough examination and debate. Hence, the best approaches for both short-term and long-term flood predictions are presented in this work. Also included are the most important developments in enhancing the accuracy of flood prediction models. The most successful tactics for improving ML algorithms have been identified as hybridizations, data decompositions, algorithm ensembles, and model optimizations. Hydrologists and climate scientists may use this survey as a roadmap to choose the best ML strategy for each prediction challenge [9].

Worldwide, floods rank high among the most devastating natural catastrophes that affect people and their infrastructure. To lessen the impact of floods, it may be necessary to install a flood prediction system. The use of in-situ measurements, such as stream and rain gauges, is usually necessary for the installation and calibration of a hydrologic model in such a system. Thanks to its availability across large ungauged areas, satellite remote sensing data has recently become a good substitute for or addition to in situ observations. To better understand the geographical scope of floods and related risks in basins that are either not measured at all or have only partial measurements taken, this research aims to incorporate the most up-to-date satellite data into a distributed hydrologic model [10]. To establish and fine-tune a hydrologic model, estimate the geographic extents of flooding, and assess the likelihood of identifying flooded regions,provide an approach that relies only on satellite remote sensing data. The Nzoia basin, a subbasin of Lake Victoria in Africa, was modelled, a raster-based distributed hydrologic model. Imaging at a Moderate Resolution The spectroradiometer Thermal Emission and Reflection on Earth and in Advanced Space Distributed hydrologic model simulation of inundations regions were benchmarked using radiometers-based flood inundations maps that were developed across the region. According to the results, the distributed hydrologic model would benefit from using satellite data for inputs such as precipitations, land cover types, topography, and other products, as well as space-based flood inundation extent. In ungauged catchments, hydrologic prediction and flood control methods may be improved using optical sensor-based flooding spatial extent quantification for model calibration and evaluation [11].

Natural and man-made catastrophes affect millions of people annually. Numerous casualties, damaged or destroyed infrastructure, and societal and economic upheaval have resulted from the growing frequency of such catastrophes over the last half-century. Early scenario identification, prevention, recovery, and management are all crucial parts of a complete and targeted solution that may help keep losses to a minimum in the case of a catastrophe. To address the complexities of disasters monitoring, detection, and management, this survey paper provides an analysis of current techniques and technologies that are pertinent to a disaster scenario. These methods and technologies include Wireless sensor networks (WSN), remote sensing techniques, artificial intelligence, IoT, unmanned aerial vehicles (UAVs), and satellite imagery [12]. The communication networks are likely to be partly down in the event of an emergency resulting from a typical catastrophe scenario; hence, backup network may be very useful for disaster management and detection. Various catastrophe scenarios are covered, with an emphasis on how other networks and related technology may keep connection up. Using state-of-the-art technology for monitoring, detecting, and managing catastrophes, it offers a thorough analysis of several disasters, including landslides, forest fires, and earthquakes. It provides suitable solutions by concentrating on several criteria essential for catastrophe identification and monitoring. Additionally, it discusses catastrophe management using big data analytics. Look at a few methods and discuss their pros and cons. Possible future paths are outlined and open obstacles are noted [13].

The environmental elements that contribute to landslides are multifaceted, and they have the potential to inflict devastating human casualties and material losses. Understanding the connections between these environmental variables and landslides is, hence, crucial. Because of this, landslip vulnerability assessments assess the efficacy of combining the analytical hierarchy processes (AHP) with the normalized frequency ratios (NFR) and Cloud model (CM). Nevertheless, landslip susceptibility mapping is constantly affected by randomness and fuzziness in addition to these complicated interactions. This paper presents a new hybrid AHP-NFR-CMs approach for landslip susceptibility assessments, which could better handle fuzziness and unpredictability, and adds the CM to enhance the integrated AHP-NFR method [14]. The first step is to use remote sensing (RS) and geographic information system (GIS) technologies to collect data for all the landslides in the research region. Then, we choose 10 environmental criteria to use as landslide effect variables. To see how each landslip impact factor relates to the frequency of landslides, we utilize the AHP approach to get the overall weight of the factors, and the NFR technique to get the weights of each subclass within each component. For each grid divided using the attributions-based spatial information multi-grid methods (ASIMG), a landslip susceptibility index (LSI) can be calculated after an appropriate compositional operation is applied to the weights of the landslip impact factors and the weights of the impact factor subclass [15].

PROPOSED SYSTEM

To facilitate the delivery of Natural Disaster Management (NDM) capabilities, this section suggests a hypothetical Cloud-based method for integrating Cloud Computing with Geospatial Science. To overcome the difficulties of providing Disaster Management as a service, the suggested answer is to make use of Cloud Computing's capabilities in conjunction with complicated disaster management models. The suggested idea is divided into three main parts that each deal with a distinct part of the system. Initiating requests and receiving desired outputs after appropriate processing and execution are both made possible via the user-interfaces, which is the only point of interaction between user and the cloud-based systems. The computing, storage, and networking resources needed to run user-initiated operations and simulations are all part of the Cloud Infrastructure block. The suggested approach relies heavily on the Control Mechanism block, which regulates the whole process of processing user's requests and maintaining the Cloud infrastructures to provide the intended result optimally. Since Cloud services may be inaccessible due to communications and power outage during disasters, the IoT networks, fog, and edge computing form an extension of Cloud computing that provides certain time-critically and less compute- and data-intensive disaster-related service. Additionally, these technologies serve as a transitional data ingestion point during disasters. A user interfaces block, which provides access to various end services made possible by the system, is the first building block of the suggested conceptual solutions. This is part of the system that consumers interact with while using cloud computing; it's available via various Application Programming Interface (API)s and web services. Because it contains the system's complete function and serves as the only point of contact between users and the systems, the user interface block is crucial to the system. The block's purpose is to make it easier to start the user requests and gather the results. Inputting input parameters and seeing model output should be possible via this block, and the user should have full access to the system's functionality. Figure 1 shows the system architecture of the proposed system.

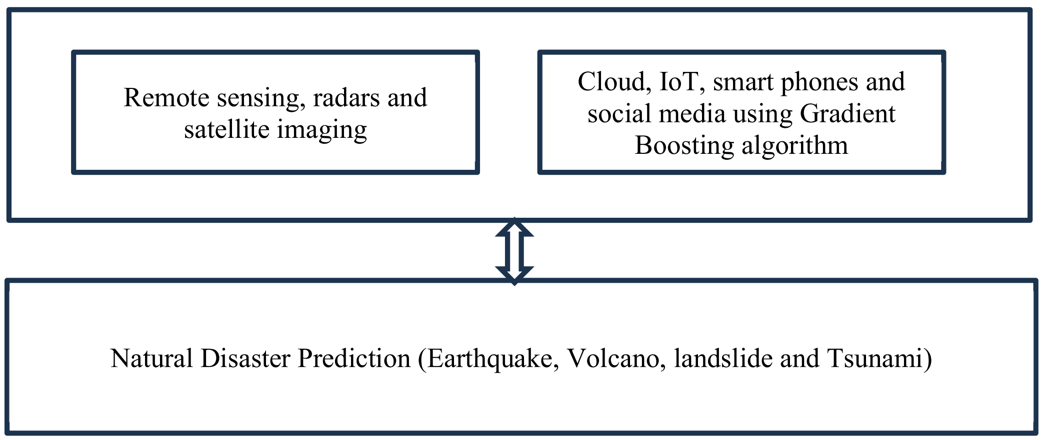

FIGURE 1. System Architecture of the Proposed System

Gather any pertinent environmental characteristics, as well as meteorological and seismic data, that pertain to past natural catastrophes. Make use of a variety of resources, including earthquake sensors, weather stations, and satellite images. Get the data ready for processing by cleaning it up and fixing any discrepancies, outliers, or missing numbers. Prepare the data so that the Gradient Boosting Algorithm may use it. To aid in the forecasting of natural catastrophes, it is necessary to extract useful characteristics from the collected data. Improve your model's performance by making use of your domain expertise to either develop new features or modify current ones.

For effective and scalable storage and processing of big datasets, use cloud systems like Amazon Web Services (AWS), Azure, or Google Cloud. When processing data, use of cloud services like databases and data lakes. Use the Gradient Boosting Algorithm to forecast the occurrence of natural disasters. Make two sets: one for training and one for validations. Use the training sets to train the models and tweak their hyper parameters until they perform as expected. Verify the model's generalizability to new data by running it through the validation set-to test how well the model holds up, use cross-validation methods. To speed up and parallelize the validation process, use resources in the cloud. Training and validating models become a breeze with cloud-based machine learning services. Set up a system to integrate data in real-time so that the model is always up to date. Make data updates a breeze by integrating cloud-based real-time data streaming providers. Create a graphical user interface to display the model's output, including forecasts and insights. Make sure both specialists and laypeople can easily use the User Interface (UI). When the model foretells a natural catastrophe is about to occur, set up an alerting mechanism to notify the proper authorities and the public. For effective and fast warning dissemination, use cloud-based messaging systems. Determine how will keep tabs on the model's progress over time. Maintaining and updating the model on a regular basis will allow it to adjust to new environmental circumstances and make more accurate predictions. This system aspires to improve the efficiency and accuracy of natural catastrophe prediction while offering a scalable and accessible solution. It does this by combining cloud services, real-time data processing, and a strong Gradient Boosting algorithm.

RESULTS AND DISCUSSIONS

If various catastrophe models can be given real-time data, they can better depict the catastrophic situations. More effective reaction to catastrophes may be achieved with higher situational awareness, which can be made possible with the updated data. IoT technology is constantly improving, making it feasible to gather real-time data during crises. Through gathering as much useful data as possible, it is feasible to set up a vast network of various sensors throughout the impacted region. Depending on the available communication methods, real-time data can be collected from a wide network of sensors during disasters like fires. These sensors can measure things like temperature, wind, humidity, rain, and fuel types. The data can also come from response teams and individuals carrying these devices, as well as from stations closer to the devices or from servers in the cloud. Cloud infrastructure offers a strong answer to many disaster-related services in the suggested solution. When catastrophes strike, this may be a problem since Cloud services rely on reliable connectivity and electricity, both of which might go down during the actual event. Considering this, Cloud computing has been explored for more time-sensitive and vital services during crises, along with new paradigms of computing such as edge and fog computing. According to the suggested method, various actions may be triggered before or during catastrophes by moving the processing of sensor data closer to the sensor network, depending on the sensitivity and complexity of the services. In the case of catastrophes when power and connection are scarce, end devices like smart phones and routers may be configured into an ad hoc network to gather vital information and do calculations to ascertain the best course of action to take in response to the crisis. In addition, local supercomputers and other on-premises computing machines, as well as HPCs (High-Performance Clusters), may be used whenever feasible. The dataset of the proposed system is shown in Table 1.

TABLE 1: Dataset of the Proposed System

Dataset	Size	Resolution	Image Type
ABCD	22171	varies	satellite
fMoW	1 million	varies	satellite
xBD	22068	1024x1024	satellite
ISBDA	1030	-	Aerial (social media)
FloodNet	2343	3000x4000	UAV

To better evaluate catastrophes, all data and processes now supported by end or local devices must be moved to the cloud infrastructures for long-term storage and more intense computing, since there are limitations in connection, power supply, and reaction time at the local level. The fundamental premise of the suggested cloud-based systems is to facilitate the use of various NDM features as end services by multiple actors (users) during the different stages of catastrophes. When compared to on-premises systems, cloud-based solutions for disaster prediction models are more cost-effective, according to many studies. Figures 2,3 and 4 show the performance of the training time, prediction time and accuracy of the proposed system.

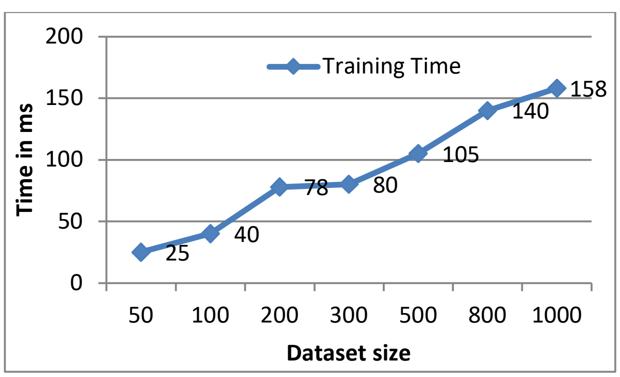

FIGURE 2. Training time Performance of the Proposed system

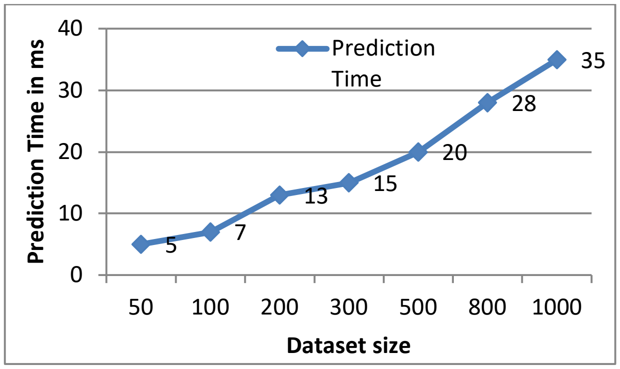

FIGURE 3. Prediction time performance of the proposed system

$$Accuracy = \frac{Correctly\ Recognized\ patterns}{Total\ patterns\ to\ Identify} * 100 \quad (1)$$

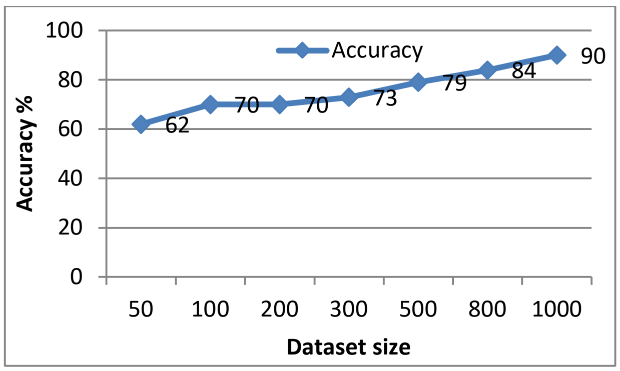

FIGURE 4. Accuracy performance of the proposed system

In addition to running disaster simulations sequentially on-premises, this work suggests running them parallelly over the cloud. This would allow us to obtain prediction results faster, allowing us more time to be better prepared for disasters. The suggested approach is efficient and cost-effective; thus, the government should be prepared to foot the bill. Here look at the various disaster model components and classify the work that has been done utilizing the ICT foundation in connection with NDM and how Cloud Computing has been adapted to assist them. A lot of research has focused on how to use different aspects of ICT, such as cloud computing, to provide various end services in the aftermath of natural catastrophes.

CONCLUSIONS

Geospatial models are becoming more computationally difficult, data processing intense, and concurrent access demanding because of the rising complexity of simulating natural processes, improvements in data collecting equipment, and advancements in web services. Offering geospatial models as a service, like NDM tools, is not feasible with the current state of ICT. The almost infinite scalability of cloud computing's compute, storage, and networking makes it an appealing platform for tackling these problems. Many different models and processing systems are available to handle different parts of disaster management, as discussed in this overview. The Cloud offers improved performance, validation, accessibility, scalability, and flexibility using Gradient Boosting algorithm; thus, these concepts and technologies are slowly making the move there. While disasters can render Cloud services unavailable owing to communication and power outages, the infrastructure that supports these services, the internet and regular power supplies—remains integral to disaster modeling and simulations that involve large amounts of data and computation. To make Cloud services more resilient in the face of disasters, Cloud Computing has expanded in the proposed frameworks to incorporate new technologies like the IoT networks, fog, and edge computing. These emerging technologies can provide essential disaster-related service and serve as a data relay for future evaluations in the Cloud.

REFERENCES

[1]. D. Ezzat, S. Abdelghafar, and A.E. Hassanien, 2021, "Applications of Deep Learning in Predicting Natural Disasters Concurrent with the COVID-19 Pandemic: Short Review and Recommendations," *The Global Environmental Effects During and Beyond COVID-19: Intelligent Computing Solutions*, pp. 105-120.

[2]. L. Tan, J. Guo, S. Mohanarajah, and K. Zhou, 2021, "Can we detect trends in natural disaster management with artificial intelligence? A review of modeling practices," *Natural Hazards*, **107**, pp. 2389-2417.

[3]. D. Huang, S. Wang, and Z. Liu, 2021, "A systematic review of prediction methods for emergency management," *International Journal of Disaster Risk Reduction*, **62**, pp. 1-5.

[4]. A.M. Vinod, D. Venkatesh, D. Kundra, N. and Jaya Pandian, 2021, "Natural disaster prediction by using image based deep learning and machine learning," *In Second International Conference on Image Processing and Capsule Networks:Springer International Publishing*, pp. 56-66.

[5]. C. Miao, and M. Ding, 2017, "Analysis of influence of natural disaster on the economy and prediction of recovery time based on grey forecasting–difference comparison model: a case study in the upper Min River," *Natural Hazards,* **85**, pp. 1135-1150.

[6]. S. Guha, R.K. Jana, and M.K. Sanyal, 2022, "Artificial neural network approaches for disaster management: A literature review," *International Journal of Disaster Risk Reduction*, pp. 1-7.

[7]. R. Ali, I. Khosa, A. Armghan, J. Arshad, S. Rabbani, N. Alsharabi, and H. Hamam, 2022, "Financial Hazard Prediction Due to Power Outages Associated with Severe Weather-Related Natural Disaster Categories," *Energies*, **15(24)**, pp. 1-6.

[8]. J.M. Kim, J. Bae, S. Son, K. Son, and S.G. Yum, 2021, "Development of a model to predict natural disaster-induced financial losses for construction projects using deep learning techniques," *Sustainability*, **13(9)**, pp. 1-8.

[9]. J.S. Mittapalli, J.A. Mutha, and R. Maheswari, 2022, "NatDisP–An Intelligent Natural Disaster Predictor," *Research Squre*, pp. 1-7.

[10]. P. Cui, J. Peng, P. Shi, H. Tang, C. Ouyang, Q. Zou, L. Liu, C. Li, and Y. Lei, 2021, "Scientific challenges of research on natural hazards and disaster risk," *Geography and Sustainability*, **2(3)**, pp. 216-223.

[11]. M. Haggag, A. S. Siam, W. El-Dakhakhni, P. Coulibaly, and E. Hassini, 2021, "A deep learning model for predicting climate-induced disasters," *Natural Hazards*, **107**, pp. 1009-1034.

[12]. J.M. Kim, S.G. Yum, H. Park, and J. Bae, 2022, "Strategic framework for natural disaster risk mitigation using deep learning and cost-benefit analysis," *Natural Hazards and Earth System Sciences*, **22(6)**, pp. 2131-2144.

[13]. X. Ge, Y. Yang, J. Chen, W. Li, Z. Huang, W. Zhang, and L. Peng, 2022, "Disaster prediction knowledge graph based on multi-source spatio-temporal information," *Remote Sensing*, **14(5)**, pp. 1-21.

[14]. M.H. Abdullah, and Z. Hamodat, 2023, "Iot Techniques for Disaster Prediction and Prevention," *International Journal of Intelligent Systems and Applications in Engineering*, **11(9)**, pp. 34-45.

[15]. J.M. Kim, S.G. Yum, H. Park, and J. Bae, 2021, "A deep learning algorithm-driven approach to predicting repair costs associated with natural disaster indicators: The case of accommodation facilities," *Journal of Building Engineering*, **42**, pp 1-6.