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Research Article

Implication of Artificial Intelligence to Determine Natural Disaster

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ABSTRACT
Nature has been a very variable as its prediction has less accuracy. Artificial intelligence has been employed to predict the weather with optimum accuracy early hand to be prepared for any natural disaster that may about to occur. Early warning signal enables inhabitants to evacuate the place that is predicted to get affected. This paper will use different machine learning algorithms using different parameters like temperature, humidity, wind velocity, direction, etc. to feed the neural network and predict the occurrence of natural disaster. Comparative study will help to analyze efficiency of different machine learning algorithms in detecting and predicting the intensity of natural disaster. Further it will also classify the prediction of type of natural disaster like volcano, earthquake, flood, tsunami, etc.

Keywords: limited resource, efficiency, detection, machine learning, algorithms

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1. INTRODUCTION

Natural disasters are significant adverse events resulting from natural hazards, impacting human life, property, and the environment. They encompass a range of phenomena, including earthquakes, floods, hurricanes, and pandemics, which can lead to fatalities, injuries, and socio-economic disruption. Understanding their frequency, causes, and effects is crucial for effective mitigation and response strategies.

Types of Natural Disasters
Geophysical: Earthquakes and volcanic eruptions, often leading to substantial casualties and property damage (Tin et al.,2024).
Hydrological: Floods and tsunamis, which are the most common disasters recorded, particularly affecting regions like Asia (Tin et al.,2024).
Climatological: Hurricanes and droughts, exacerbated by climate change, increasing their frequency and intensity (Dhanesh and Sriramesh,2016).

Socioeconomic Impacts
Natural disasters can disrupt tourism, affecting consumer behaviour and industry operations, as seen during the COVID-19 pandemic and the 2004 Indian Ocean tsunami (Boskey,2003).

They exacerbate existing social inequalities, influencing recovery and resilience based on demographic factors such as age and socioeconomic status (Shtob,2002).

Artificial intelligence (AI) refers to the capability of machines to perform tasks that typically require human intelligence, such as reasoning, learning, and problem-solving. It encompasses various functions, including perception, synthesis, and inference of information, which are demonstrated through tasks like speech recognition and computer vision. The Oxford English Dictionary defines AI as the science focused on developing programs or machines that can reason independently and solve problems more efficiently than humans (Morandín-Ahuerma,2024).

Key Characteristics of AI
Cognitive Abilities: AI systems can simulate human cognitive functions, enabling them to learn and adapt over time (Morandín-Ahuerma,2024).
Autonomy Levels: AI can be categorized based on its autonomy, ranging from reactive systems to fully autonomous agents (Morandín-Ahuerma,2024).

Applications: Common applications include language translation, image recognition, and data analysis, showcasing AI's versatility (Nabeel,2023).
The role of artificial intelligence (AI) in natural disaster management is increasingly vital as the frequency and severity of such events rise. AI technologies enhance disaster preparedness, response, and recovery efforts by leveraging data analytics, predictive modeling, and real-time monitoring. This integration not only improves decision-making but also fosters resilience against climate-related disasters.

Predictive Analytics and Early Warning Systems
AI algorithms analyze historical and real-time data to predict disasters like floods and earthquakes, enabling timely alerts (Venkadesh et al.,2024). Machine learning enhances early warning systems, optimizing resource allocation and response strategies (Gobinath et al.,2024).

Real-Time Monitoring and Damage Assessment
AI facilitates remote sensing and satellite imagery analysis, providing accurate disaster monitoring (Venkadesh et al.,2024). Post-disaster, AI aids in damage assessment, helping to prioritize recovery efforts and resource distribution (Satishkumar and Sivaraja,2024).

Community Engagement and Social Media Integration
AI systems can analyse social media data to gauge public sentiment and gather real-time information during disasters (Venkadesh et al.,2024).
This community-centric approach enhances the effectiveness of response efforts by incorporating local knowledge and experiences (Venkadesh et al.,2024).

While AI offers transformative potential in disaster management, challenges such as ethical considerations and the need for interdisciplinary collaboration remain critical for successful implementation.
This chapter enlighten the assumption of natural disasters by artificial intelligence.

AI in flood detection
AI technologies are increasingly being utilized for flood detection, leveraging advanced machine learning models and sensor integration to enhance accuracy and response times. These systems utilize various methodologies, including deep learning frameworks and IoT devices, to provide timely and reliable flood information.

Deep Learning Approaches
Semantic Segmentation: Systems like U-Net have been employed to analyze aerial and satellite images, achieving an Intersection over Union (IoU) score of 0.85, which surpasses traditional methods (Chandran et al., 2024).
Explainable AI (XAI): Techniques such as Grad-CAM and perturbation-based methods enhance the interpretability of flood detection models, ensuring stakeholders can trust the predictions made by complex models(Τέμενος et al., 2024; Schlegel & Hänsch, 2024).
Comparative Studies
Multi-Modal Techniques: Research comparing various AI methods, including DCNN and traditional models, indicates that multi-temporal datasets can significantly improve flood detection accuracy, achieving an F1 score of 0.8846(Sonavale et al., 2024).
While AI offers promising advancements in flood detection, challenges remain in ensuring model transparency and integrating diverse data sources effectively. Balancing accuracy with interpretability is crucial for stakeholder trust and operational success.

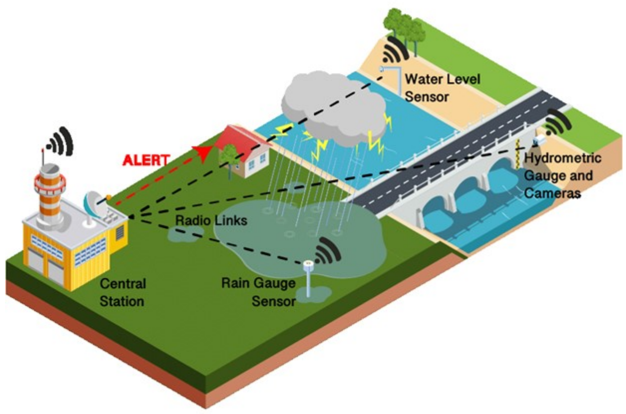

Fig. 1 Image of early flood detection (Esposito et al.,2022)

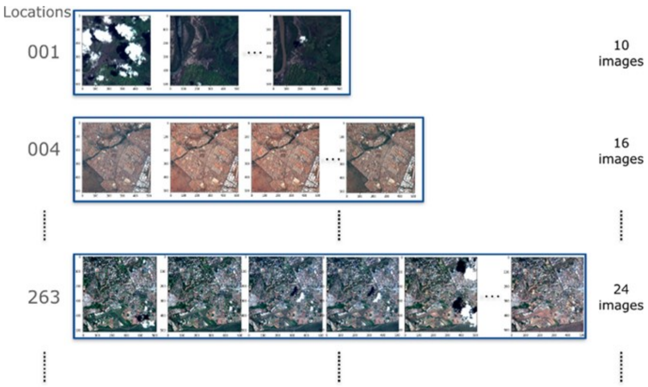

Fig. 2 Flood detection from satellite images using deep learning (Institute of Cartography and geoinformatics, faculty of Civil Engineering and Geodetic Science)

AI earthquake detection

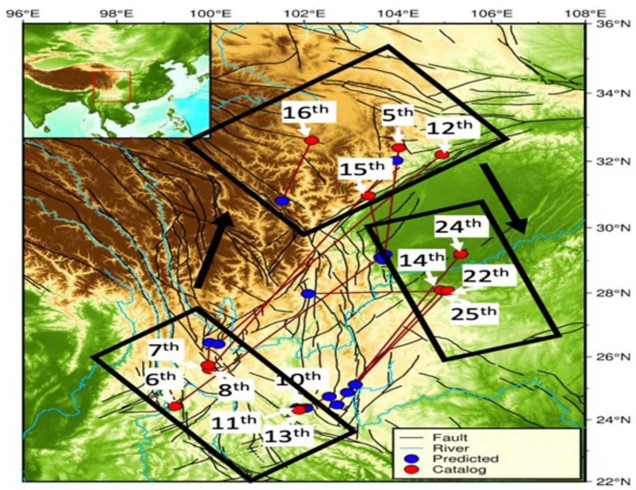

Fig. 3 AI-Driven Earthquake Forecasting Shows Promise in Trials (Texas Geosciences, University of Texas at Austin)

AI technologies are increasingly being utilized for earthquake detection, enhancing the accuracy and efficiency of seismic monitoring. Various machine learning and deep learning models have been developed to improve detection capabilities, particularly in environments with sparse data. The following sections outline key advancements in AI-driven earthquake detection methods.

Deep Learning Approaches
EQTransformer: This model employs a complex method with Monte Carlo Dropout, yielding more reliable detections compared to simpler methods, which are prone to false positives(Gamboa-Chacón et al., 2024).

TransQuake: This innovative model integrates STA/LTA algorithms with a multi-head attention mechanism, demonstrating superior performance in detecting seismic waves from the 2008 Wenchuan earthquake dataset(Gai et al., 2024).

Real-Time Monitoring
GNSS Ionospheric Seismology:
Utilizing deep learning for real-time detection of ionospheric disturbances caused by seismic events, this approach significantly enhances tsunami early warning systems, achieving high accuracy in TID identification (Ravanelli et al., 2024).

Computer Vision Techniques
SUGAR: This method employs 3D image segmentation to detect and locate seismic sources, outperforming traditional analysis methods in complex aftershock sequences, as demonstrated in the 2016 Kaikōura earthquake(Tan et al., 2024).

While AI methods show promise in improving earthquake detection, challenges remain, particularly in data sparsity and the need for extensive training datasets. Continued research is essential to address these limitations and enhance the robustness of AI applications in seismology.

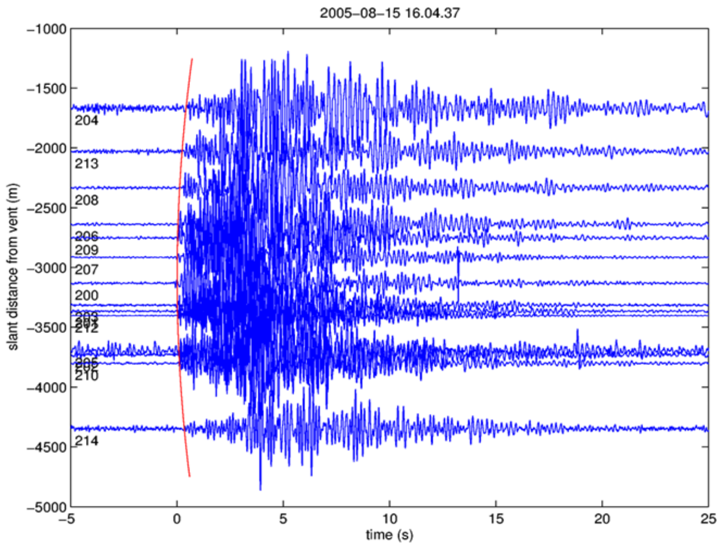

Fig. 4 Earthquake seismic vibration (Konahi)

AI and IoT technologies are increasingly being integrated into earthquake detection systems to enhance early warning capabilities and disaster management. These systems utilize various sensors and machine learning algorithms to analyze seismic data, providing timely alerts to mitigate the impact of earthquakes.
Sensor Technologies

Accelerometers: Devices like the ADXL335 are employed to capture multi-axis accelerations, which are crucial for detecting seismic activity(Amat et al., 2024).
MEMS Sensors: Micro-electromechanical systems (MEMS) sensors are used for monitoring seismic events, offering a cost-effective solution for dense monitoring networks(Lee et al., 2022).
Machine Learning Applications
Predictive Analytics: Machine learning models, including decision trees and support vector machines, analyze accelerometer data to predict potential earthquakes(Amat et al., 2024).
Deep Learning: Advanced AI techniques, such as deep reinforcement learning, automate the earthquake location process, improving accuracy in identifying seismic events(Kuang et al., 2023).
Data Utilization
Open Datasets: The establishment of publicly available datasets from IoT-based seismic data enhances the training of AI models, improving detection accuracy.
While these technologies show promise in enhancing earthquake detection and response, challenges remain in ensuring data quality and system reliability, particularly in densely populated urban areas(Lee et al.,2022).
AI in temperature determination

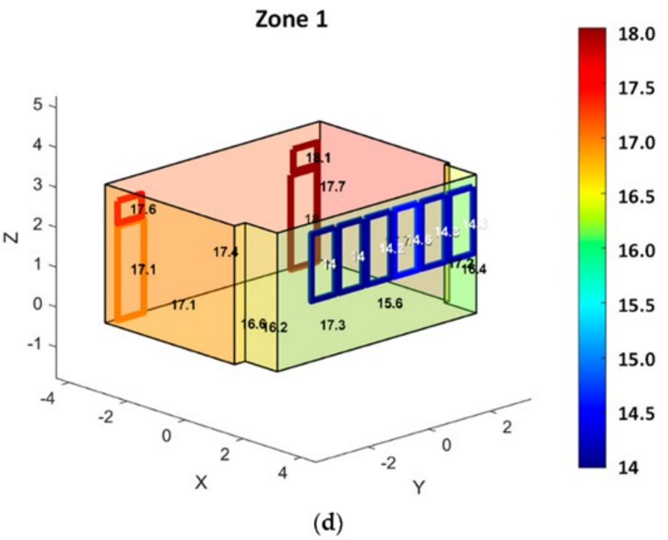

Fig. 5 Temperature measurement using AI (Adán et al., 2023).

AI technologies are increasingly being utilized for temperature determination across various applications, enhancing accuracy and efficiency compared to traditional methods. By leveraging machine learning algorithms and artificial neural networks (ANNs), researchers have developed innovative approaches that address the limitations of conventional temperature measurement techniques.

AI Techniques in Temperature Measurement
Natural Frequencies and AI: A study integrated modal parameters with AI to estimate temperature variations, achieving a maximum predicted deviation of 0.386 °C, significantly improving accuracy over traditional methods(Aman et al., 2023).

Geothermal Applications: Machine learning algorithms, particularly random forest and fuzzy logic, were employed to predict static formation temperatures in geothermal fields, with the random forest algorithm achieving a mean absolute error (MAE) of 0.7% (Al-Fakih & Kaka, 2023).

Battery Temperature Estimation: An ANN was used to estimate the core temperature of lithium-ion cells based on electrochemical impedance data, achieving an accuracy of approximately 1 K, which is crucial for battery safety (Ströbel et al., 2023).

Raman Distributed Sensors: An ANN improved the temperature accuracy of a long-range Raman Distributed Sensor, reducing the error from 43.19 °K to 4.21 °K over a 50 km distance (Pradhan, 2023).

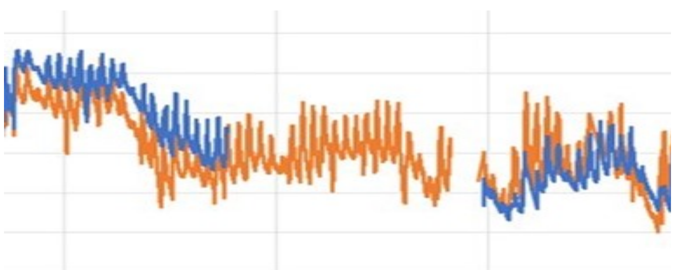

Fig.6 Determination of air temperature (Peterková et al., 2019).

AI in humidity
Artificial intelligence (AI) is increasingly being utilized to optimize humidity control across various applications, including indoor environments and agricultural settings. By leveraging AI algorithms, systems can autonomously adjust humidity levels based on real-time data, enhancing both comfort and efficiency. The following sections outline key applications of AI in humidity management.

AI in Indoor Humidity Control
AI technologies, such as the Econavi system, integrate sensors to autonomously regulate indoor humidity levels, improving air quality and energy efficiency.

Experimental analyses demonstrate that AI can effectively maintain desired humidity levels, contributing to advancements in smart home technologies.

AI in Agricultural Humidity Management
In greenhouse applications, packed bed systems utilizing water as a working fluid have shown a 50% increase in humidity, significantly enhancing crop yields(Bhowmik et al., 2024).
AI-based models, particularly multi-layer perceptron neural networks, have been developed to assess the performance of these systems under varying conditions, achieving high prediction accuracy(Bhowmik et al., 2024).

AI for Humidity Measurement in Air Conditioning
AI methodologies, such as artificial neural networks, have been employed to derive relative humidity from parameters like temperature and air volume, achieving a maximum error of less than 4.5%(Yang et al., 2024).
This approach addresses the limitations of traditional humidity sensors, making it suitable for practical air conditioning applications.
While AI presents significant advancements in humidity control, challenges remain in sensor reliability and the integration of these technologies into existing systems. Further research is needed to enhance the robustness and applicability of AI solutions in diverse environments.

AI in tsunami detection
Machine learning techniques significantly enhance the real-time monitoring of tsunami waves by leveraging advanced data analysis methods to detect and predict tsunami-related disturbances. These techniques improve the accuracy and efficiency of tsunami early warning systems (TEWS), particularly in open-ocean regions where traditional buoy systems are ineffective. The following sections outline the key contributions of machine learning in this domain.

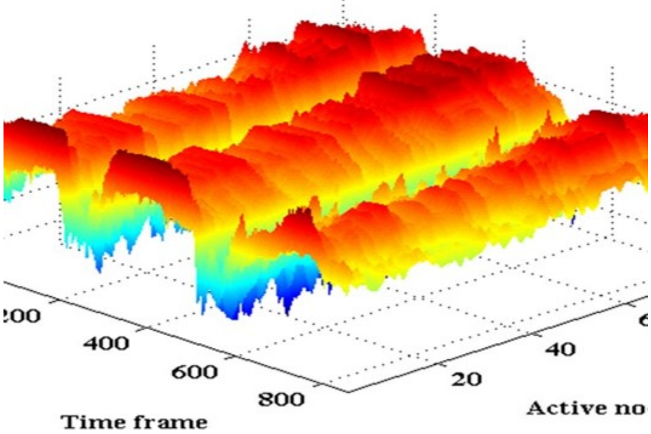

Fig. 8 Data driven humidity plotting of an area (Imanian et al., 2021).

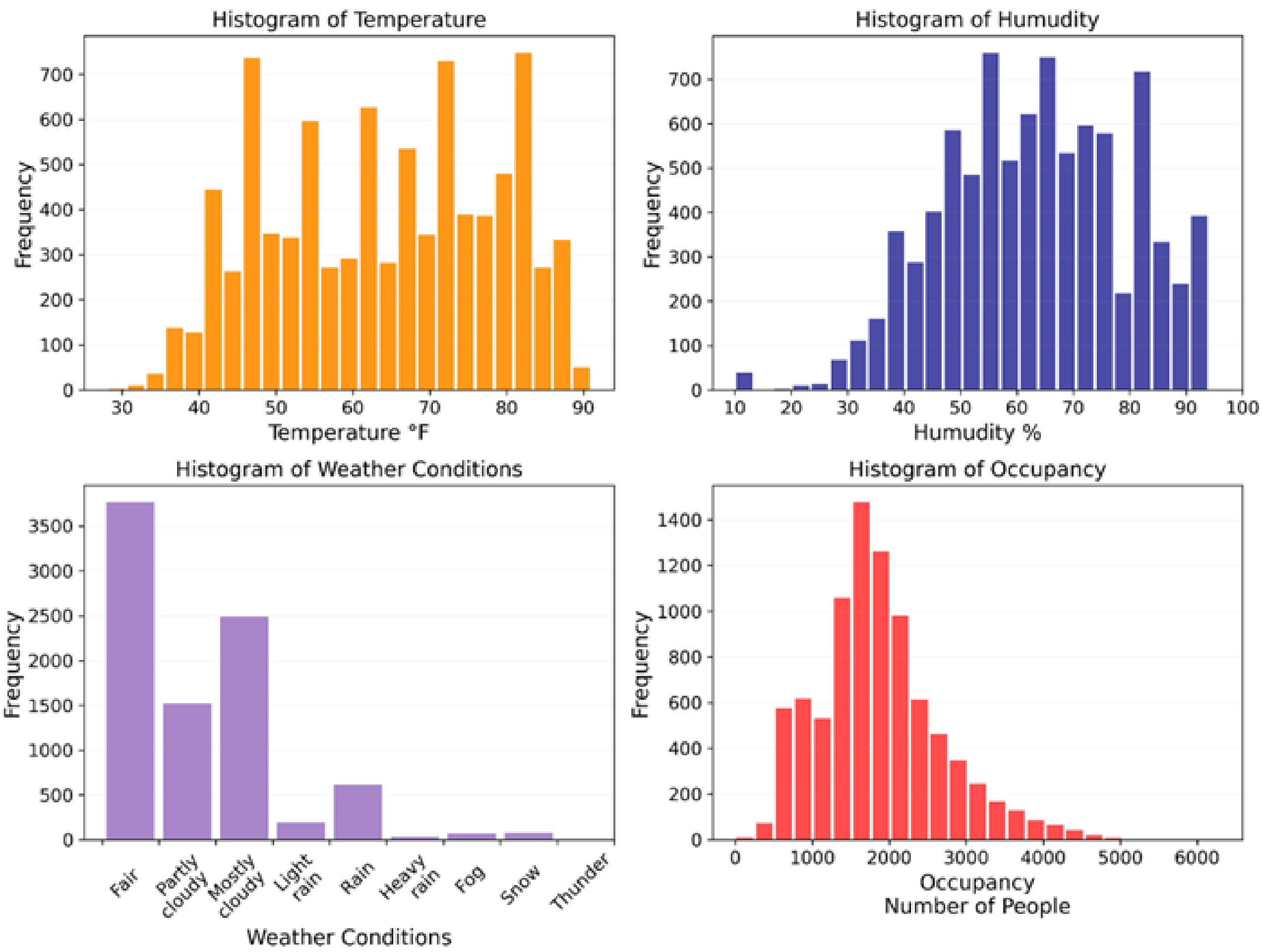

Fig. 7: Determination of humidity (Yayla et al.,2022).

Real-Time Detection of Ionospheric Disturbances
Machine learning algorithms, such as Convolutional Neural Networks (CNNs) and XGBoost, are employed to analyze Total Electron Content (TEC) variations caused by tsunamis, known as Traveling Ionospheric Disturbances (TIDs) (Ravanelli et al., 2024; Fuso et al., 2024).

The VARION algorithm processes data from GNSS stations, enabling automated detection of TIDs with high accuracy, achieving F1 scores of up to 91.7% (Ravanelli et al., 2024; Constantinou et al., 2023).

Enhanced Tsunami Forecasting
Regression tree models are utilized to forecast tsunami wave heights based on pre-computed simulation data, providing interpretable results that aid decision-making in TEWS (Cesario et al., 2024).

These models can efficiently handle large datasets, improving computational speed and accuracy in predicting tsunami impacts (Cesario et al., 2024).

While machine learning offers substantial advancements in tsunami monitoring, challenges remain, such as the need for extensive training data and the potential for model overfitting. Addressing these issues is crucial for further enhancing the reliability of tsunami early warning systems.

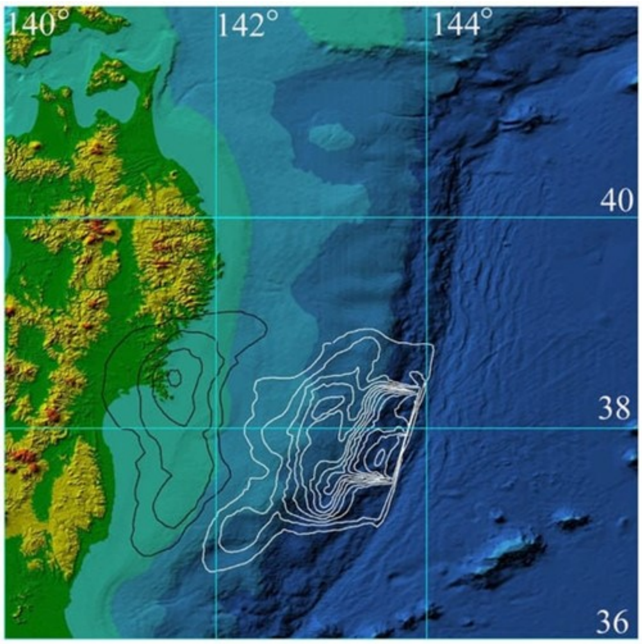

Fig. 9 Geospatial image of an area (Lavrentiev et al.,2022).

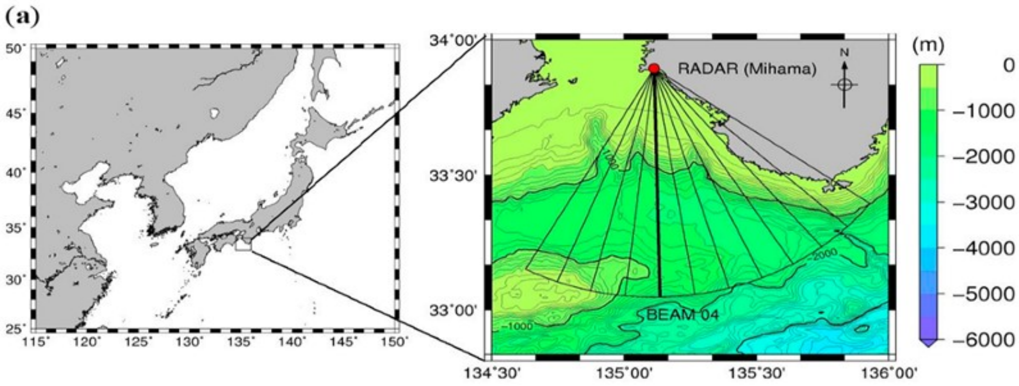

Fig. 10 Radar based image detection (Ogata et al.,2018).

Neural network efficient to determine natural disaster
Neural networks play a crucial role in enhancing the prediction and management of natural disasters. Various architectures, particularly Artificial Neural Networks (ANNs) and Convolutional Neural Networks (CNNs), have been effectively utilized to analyse data and automate processes related to disaster response.
Artificial Neural Networks (ANNs)
ANNs are pivotal in predicting natural disasters by analysing environmental, geological, and meteorological data.
They enable the development of early warning systems, allowing communities to prepare and respond effectively to impending disasters [Gobinath et al.,2024,Deborah, et al.,2024].

Convolutional Neural Networks (CNNs)
CNNs excel in image classification tasks, particularly in identifying and categorizing disaster-related images, such as those from earthquakes and floods.
A stacked CNN ensemble approach achieved 95% accuracy in classifying disaster images, demonstrating their effectiveness in damage assessment and recovery management [Rathod et al.,2023].
Deep Learning for Fire Detection
Deep Neural Networks have been employed for fire detection, crucial for managing wildfires exacerbated by climate change.
A new evaluation metric, Image-level mean Average Precision (ImAP), was proposed to better assess fire detection capabilities, highlighting the need for reliable detection systems in disaster management [Tzimas et al.,2023].
While neural networks significantly enhance disaster prediction and management, challenges remain in data integration and real-time decision-making, necessitating ongoing research and development in this field.
Benefits and challenges of AI to determine natural disaster
The integration of artificial intelligence (AI) in predicting natural disasters offers significant benefits, enhancing preparedness, response, and recovery efforts. AI technologies, particularly machine learning (ML), enable the analysis of vast datasets to improve prediction accuracy and timeliness, ultimately saving lives and reducing economic impacts.

Enhanced Prediction Capabilities
AI algorithms, such as artificial neural networks (ANNs), utilize historical data and real-time information to forecast disasters like earthquakes and floods, allowing communities to prepare effectively (Gobinath et al.,2024).
Machine learning models can analyse critical factors, including weather patterns and infrastructure vulnerabilities, leading to more informed decision-making during disaster management [Satishkumar, D., & Sivaraja,,2024].

Improved Resource Allocation
AI facilitates efficient resource allocation during disaster response by optimizing logistics and identifying areas most in need of assistance [Venkadesh et al.,2024].
The integration of social media data into AI models provides real-time insights, enhancing situational awareness and community engagement during crises [Venkadesh et al.,2024].

Holistic Disaster Management
AI supports a comprehensive understanding of interconnected hazards, fostering a proactive approach to disaster management that incorporates local knowledge and expertise [Venkadesh et al.,2024].
The use of remote sensing and satellite imagery in conjunction with AI enhances monitoring and damage assessment, leading to quicker recovery efforts [Satishkumar, D., & Sivaraja,2024].
While the benefits of AI in disaster prediction are substantial, challenges such as data privacy, algorithmic bias, and the need for robust infrastructure must also be addressed to ensure effective implementation and community trust in these technologies.

Conclusion
In conclusion, the integration of artificial intelligence and machine learning algorithms in disaster prediction and early warning systems has proven to be a game-changer in mitigating the impact of natural disasters. By leveraging diverse parameters such as temperature and humidity these systems can effectively feed neural networks to provide accurate predictions about the occurrence, intensity, and type of natural disasters. The comparative analysis of various machine learning algorithms highlights their relative efficiency and accuracy, offering valuable insights into selecting the most suitable approach for specific disaster scenarios. Also, the ability to classify disasters such as earthquakes, floods, and tsunamis ensures targeted responses and preparedness. Ultimately, this approach significantly enhances disaster management efforts, saving lives and minimizing economic and environmental damages.

Consent for publication
Yes

NOC from all authors
Yes

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