**Prediction of Seismic Exertion in the Subduction Zones Using Artificial Neural Networks**

**ABSTRACT**

This paper presents a data-driven approach to efficiently and accurately predict tsunamis caused by underwater earthquakes (EQ). A data-driven prediction model was developed using artificial neural networks (ANN) using pre-calculated tsunami scenarios as the training data set. The training data covers various earthquake magnitudes and locations and provides detailed information for the ANN method. Tests confirm the effectiveness of the method and demonstrate its ability to accurately and almost accurately predict the height and arrival time of the maximum tsunami in all calculations. Data prediction models that use neural networks to capture relationships in data sets and increase the power of predictions are always more insightful than traditional methods. This approach will increase the effectiveness and efficiency of tsunami forecasting by integrating neural networks into the forecasting process, which is necessary to prevent disasters and reduce long-term damage and underwater repercussions in coastal waters. The ability to predict a tsunami's height and arrival time allows authorities to issue timely warnings and implement evacuation measures, reducing the impact on lives and buildings. Overall, this article demonstrates the potential of data-driven approaches, especially artificial intelligence, to improve tsunami forecast accuracy, coastal safety, and disaster management strategy.

**Keywords** Earthquake, Artificial Neural Networks, Tsunami, Subduction Zones, Seismic Exertion, Earthquake prediction.

**Introduction**

Today's society faces a serious threat from natural disasters, which is why preparation is essential to lessen their impact. The public has launched several campaigns in recent years to lessen the harm that these calamities due to the economy and people's lives. Modern awareness is ingrained with the idea of a natural calamity. The concept of risk remains a contentious issue to this day. To address issues brought on by natural catastrophes, risk assessment and management techniques are crucial. This is because the hazard's nature is frequently seen as a measure of it.

Natural catastrophes happen when threatening circumstances materialize. Earthquakes are the most significant natural disasters due to the significant losses they inflict when compared to other catastrophes like tsunamis, forest fires, hurricanes, typhoons, and floods. Earthquakes happen quickly and may wipe out an entire city or region in a matter of seconds. They can also cause environmental or economic harm in addition to death and devastation. Furthermore, a lot of locations are in an earthquake zone. In addition, landslides, liquefaction, tsunamis, and other effects can result from earthquakes.

Seismic risk is a measure of the danger posed by an earthquake and is the result of a combination of adverse and actual seismic events. The devastating impact of earthquakes and related events underscores the urgent need to address social problems. Understanding earthquakes requires understanding the geological processes that allow energy to be released from the Earth's rocks. Earthquakes occur when energy is suddenly released as a fault in the ground rock, causing ground shaking and potential damage.

Many types of seismic events occur, including tectonic earthquakes caused by the movement of tectonic plates, volcanic seismicity associated with volcanoes, and earthquakes caused by human activities such as reservoir-induced earthquakes caused by mining or filling. Large earthquake reservoirs. Each type of seismic event presents different challenges and requires mitigation strategies. A better understanding of the mechanisms and characteristics of different earthquake events allows communities to improve disaster prevention and mitigation efforts. These measures are designed to reduce the impact of earthquakes, strengthen earthquake resilience and ultimately protect life and property.

In addition to conventional reaction techniques, the most basic data-driven tsunami forecasting system comprises a library of preconditions and case selection techniques. To choose the best event in the data, historical events are compared with wave meters close to the earthquake location. Various scientists have offered various recommendations. The assumption that the propagation of tsunami waves is linear through the linear superposition of pre-computed data limits this approach. An ANN-based method for forecasting the Indian Ocean tsunami's arrival timing. Predicting tsunami height with a Generalized Regression Neural Network (GRNN). The use of the tsunami model as a nonlinear process to provide scenario information is made possible by this method, albeit it is only applicable to a few initial observations.

This important EQ work has time to enter from the previous earthquake distribution. This physical distribution describes the frequency of seismic events as a function of their magnitude [1]. These measurements show the relationship between the geophysical reality of seismic inertia [2], the Gutenberg-Richter law [3], and the foreshock frequency [4]. Regardless of the degree of nonlinearity between seismicity and geophysical reality, the relationship between them must be modelled. Seismic silence eliminates the physical seismic energy released by the fault area. The accumulation of energy on faults can cause earthquakes, and the stored energy is related to the magnitude of future earthquakes [5]. Similarly, foreshock frequency is also considered a sign of major earthquakes [6]. The front shock absorber is EQ and is smaller than the shock absorber. The modified Gutenberg-Richter law states that the relationship between earthquakes and their frequencies is less than or equal to proximity [7].

Scientific advancement in several fields has lagged for a while. However, new developments in neural networks have completely changed our capacity to spot patterns in intricate data that come from several sources. We can fulfil our aims with enormous potential thanks to the deep learning made possible by this technology, particularly in scenarios like pre-earthquake forecasts where complex data is difficult for models to collect and data is not static. The inability of traditional seismic detection techniques to detect low seismic noise concealed events highlights the pressing need for novel techniques, like deep learning, to further our knowledge of seismology and forecasting.

Machine Learning (ML) and Artificial Neural Networks, computer vision [8], object recognition [9], genetics [10], bioinformatics [11], weather forecasting [12], etc. It is widely used in many areas such as. Application form. On. This technology is used for many purposes, including information sharing and analysis. Scientists are currently investigating the ability of neural networks to model the relationship between geophysical events and the concept of intelligence. Using the power of neural networks, researchers aim to uncover the complexities and inconsistencies in this relationship, leading to better understanding and advances in research in world science and philosophy.

The devastating earthquake and tsunami in Japan in 2011 were the ninth-largest natural disaster and caused an estimated $360 billion in damage and economic losses. Among these disasters, the 2004 Sumatra-Andaman earthquake was the most dangerous, with a magnitude of 9.1 to 9.3 [13] [14] [15]. It is difficult to quantify the initial losses from this seismic event; Estimates range from $12.5 billion to $150 billion, reflecting the difficulty of assessing the economic costs associated with such a disaster. The epicentre was located near the north western coast of Sumatra, Indonesia, indicating the earthquake event that occurred in the Indian Ocean on December 26, 2004 [16].

**Literature Reviews**

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|  | **Title** | **Methodology** | **Evaluation** | **Limitations** |
| 1 | A probabilistic neural network for earthquake magnitude prediction [17] | Probabilistic neural networks (PNN) work using Bayesian statistics and nonlinear estimators. It relies on eight seismicity indicators for forecasting, eliminating the need for multiple levels of training. | The model predicts earthquakes using seismic indicators, correctly forecasting 2 out of 4 earthquakes and making no false predictions for magnitude 6.0 to 6.5 quakes. It also forecasted 63 out of 127 earthquakes with magnitudes between 5.0 and 5.5. | This model does not predict earthquakes larger than magnitude 6.0. |
| 2 | Artificial neural network for tsunami forecasting [18] | Two ANN models, one predicting maximum wave height and the other arrival time, were trained using spatial data, including simulations from the TUNAMI-N2-NUS model for potential seafloor rupture scenarios. | Good agreement was found between ANN predictions and TUNAMI-N2-NUS simulations for arrival time and maximum wave height. Increasing resolution in error-prone areas may reduce prediction errors. ANN for Tsunami Forecasting offers fast results and aligns well with TUNAMI-N2-NUS modeling. | These errors are more noticeable in shallow waters near shore, and correcting the problem in these areas can help reduce the estimate. |
| 3 | Earthquake Aftershocks Pattern Prediction [19] | Deep learning, using tools like Keras, Theano, and TensorFlow, is applied in seismology for detecting, predicting, and modeling seismic waves and aftershocks. Models like Pattern Recognition Neural Network, Recurrent Neural Network, Random Forest, and Linear Programming Boost Ensemble Classifier are commonly used for post-processing tasks. | The analysis utilized seismic data from the US Geological Survey (USGS)-National Earthquake Information Center (NEIC) and other open data sources to detect earthquakes causing post-main shock damage. | Does not provide specific details on the exact deep learning models or algorithms used |
| 4 | Earthquake magnitude prediction in Hindukush region  using machine learning techniques [20] | Deep learning methods, using Keras, Theano, and TensorFlow, are applied in seismology to identify, predict, and model seismic waves and aftershocks, utilizing various models including neural networks, recurrent neural networks, random forests, and ensemble classifiers. | Machine learning varies in performance metrics. LPBoost is most accurate.  PRNN achieves 71% predictive value. Over 132 months, 68 had earthquakes above 5.5 magnitude, with a 52% epicenter rate. | The study didn't compare machine learning with traditional earthquake prediction methods. Results may be region-specific to Hindu Kush and not easily applicable elsewhere without further analysis and simulation. |
| 5 | Earthquake prediction in California using regression algorithms and cloud-based big data infrastructure [21] | The study examines California events from 1970 to 2017, employing regression algorithms including GLM, GBM, DL, and RF. Stacking is utilized with RF as the base learner. Big data in public cloud is used for processing and analysis. | The study aims to predict the largest earthquake in California within the next seven days using a 1 GB earthquake catalog. Given the substantial financial resources required for such predictions, big data and methods are crucial. Random Forest exhibited the most promising results among the tests, leading to the creation of a combined model to enhance forecasts. | The estimate is limited to California, potentially restricting the generalizability of findings to other regions. Utilizing big data may pose challenges in access and costs for researchers with limited resources. Additionally, the study lacks a comparison of various regression algorithms in earthquake prediction scenarios. |
| 6 | Earthquake prediction model using support vector regressor and hybrid neural networks [22] | The study employs SVR and HNN for earthquake prediction, with comprehensive training including seismic feature calculation, selection, and model training. It integrates seismic signature calculation and custom selection, utilizing geophysical and seismological facts for robust parameter computation. Evaluation across multiple regions ensures thorough assessment of the model's capabilities. | This research proposes the SVR-HNN estimator for regional earthquake prediction, showcasing the effectiveness of combining SVR and HNN for this purpose. | Data integration enhances prediction model results with detailed evaluation methods. While primarily retrospective, real-world testing of the model's predictions can offer valuable insights and spur further exploration. |
| 7 | Earthquake Prediction using Convolutional Neural Network [23] | Authors used previous data, performed feature extraction with CNNs, trained models, and predicted earthquakes. They specifically trained CNN models for earthquake prediction using seismic data. | The CNN model achieved an impressive 87% accuracy in earthquake prediction, showcasing its ability to identify seismic patterns and uncertainties, thereby enhancing data accuracy. | The effectiveness of CNN models in earthquake prediction is limited by the specific data and parameters used in this study. |
| 8 | Earthquakes magnitude predication using artificial neural network in northern Red Sea area [24] | The study utilized Logsig, Tansig, and Purelin replacement ANN designs. Two percentage methods for comparison were employed, along with statistical methods like linear, quadratic, and cubic regression. Performance was measured using MAE and MSE. | The study is based on random distribution. Increasing standard deviation worsens random distribution prediction performance, while higher variance improves it. Various statistical methods, including linear, quadratic, and cubic regression, were used for data fitting. The neural network model exhibited superior accuracy, with at least 32% higher prediction accuracy compared to other methods. | The study utilized a deep feedforward neural network, also known as multilayer perceptron (MLP). Parameters like the number of hidden layers, neurons per layer, and activation selection were selected to balance model complexity with predictive performance. The focus was on predicting major earthquakes, excluding investigation into other earthquake predictions or potential hazards. |
| 9 | Neural network applications in earthquake prediction (1994-2019): Meta‐analytic and statistical insights on their limitations [25] | A systematic review analyzed 77 articles on neural networks (ANNs) in earthquake prediction from 1994 to 2019. It focused on performance metrics like accuracy, positive accuracy, negative accuracy, and R-score as documented in the literature. | Most studies confirm positive results, demonstrating the effectiveness of ANN models in earthquake prediction. R scores, though varying, are always above zero. Only 47% of studies compare ANN performance to baseline models, with 22% using bases like Poisson's null hypothesis or random data. ANN is typically preferred over other classifiers like decision trees, support vector machines, and k-nearest neighbors. | ANNs for earthquake prediction encounter challenges including performance, uncertainty, and lack of repeatability due to limited samples and model quality. Black box nature adds interpretation uncertainty, necessitating simple corrections and guarding against model selection bias. These issues stress the need for careful consideration and transparency in ANN usage. |
| 10 | Application of a new machine learning model to improve earthquake ground motion predictions [26] | A new hybrid stacked machine learning model called SeisEML (Seismic Integrated Machine Learning) has been introduced. Feature selection minimizes MAE and RMSE over time. Model training utilizes XGBoost, with integration of methods including XGB, LGBM, CatB, RF, SGWO, BO, K-RR, and RR. | SeisEML outperforms GPR, Extra Tree Regressor, Random Subspace Catboost, AdaBoost, and Decision Tree models in prediction accuracy. It also excels in data statistics like R^2 (0.77) and MAE (0.123) compared to other single test models. | SeisEML's integration of diverse study histories and methods can complicate interpretation and application. Moreover, its computational demands for training and reasoning are significant. |
| 11 | Earthquake prediction from seismic indicators using tree‑based ensemble learning [27] | Integrated tree-based classifiers like CatBoost are employed for earthquake prediction using seismic indicators. The Boruta-Shap feature selection method determines crucial seismic parameters for earthquake prediction across three regions: Hindu Kush, Chile, and Southern California. | The Chile earthquake prediction model outperforms those for Hindu Kush and Southern California, despite Southern California having a larger dataset. Combining tree-based classification and feature selection techniques enhances prediction accuracy. These results underscore the significance of factors like data quality, feature selection, and model performance in earthquake prediction. | Data availability and inconsistency influence the effectiveness of earthquake prediction models. Regions with limited data, like Hindu Kush, often yield lower estimates compared to areas with extensive seismic monitoring. Utilizing a compound tree is computationally demanding and necessitates careful attention to hyperparameters. |
| 12 | Prediction of earthquake magnitude and seismic vulnerability mapping using artificial intelligence techniques a case study of Turkey [28] | An ANN model was developed to estimate earthquake magnitude and generate seismic damage maps. Inputs to the model include latitude, longitude, earthquake magnitude, depth, and error. Seven learning machines, including XGBoost, Random Forest, Extra Trees, Decision Trees, Bayesian Ridge, CatBoost, and LightGBM, were trained and evaluated for predicting large earthquakes. | ANN models outperform traditional machine learning models, with ANN-2 optimized using the "Adam" algorithm being the most effective in predicting major earthquakes. ANN-1 achieves an R^2 of 0.98012, ANN-2 reaches 0.98710, and ANN-3 attains 0.97847. Both ANN and ML models demonstrate predictive capabilities for seismic mapping and earthquake prediction, supported by high R^2 scores indicating their ability to explain changes in target variables. | Accurate and reliable models necessitate data analysis and modeling expertise. Their quality depends on the quantity and quality of input data for training and testing. However, limitations in data availability and quality can sometimes impact model performance. |
| 13 | The Impact of Tectonic Setting on Machine Learning Approaches [29] | LSTM, BiLSTM, and color-layered BiLSTM models are utilized to predict future seismic events using seismic datasets from Rico, Kansas, and Puerto Rico. The data includes details on seismic events, magnitude, depth, and location. Various features like seismicity rate, b value, and Gutenberg-Richter parameter are calculated to characterize seismicity in each region. | BiLSTM with the color layer model achieved good performance on the Kansas dataset with MAE of 0.080, MSE of 0.011, RMSE of 0.106, and MAPE of 22.98%. Machine learning algorithms show potential to predict earthquakes with an error rate as low as 28.87%, offering promise for global earthquake prediction improvement beyond Kansas and Puerto Rico. | The study focuses solely on seismic data from Kansas and Puerto Rico, limiting the generalizability of findings to regions with different tectonics. The effectiveness of machine learning models can be influenced by the availability and quality of seismic data, which may vary across regions. |

Researchers combine IoT, cloud, and edge computing to pioneer smart earthquake monitoring. A reliable Bayesian model is at the frontier of real-time data processing, while a weather-based adaptive neuro-fuzzy inference system (ML) predicts earthquake magnitude. The system has higher accuracy, lower latency, reliability, and stability. Timely early warning can improve community safety and support effective predictions [30]. In a systematic review from 2017 to 2021, researchers analyzed 31 studies that used machine learning (ML) to predict earthquakes. They evaluated performance across regions and dimensions and compared algorithm performance with seismic indicators. The result of the effectiveness of machine learning algorithms, which are especially good at predicting large earthquakes, shows that more research is needed in this area [31]. Researchers analyzed earthquake studies (2017-2021) using ML algorithms, evaluating the performance of 31 studies in predicting global magnitude, frequency, and natural layer. A series of machine learning algorithms and seismic measurements are evaluated, yielding useful results for earthquake prediction and informing future research. This study presents a potential algorithm developed to conduct a comprehensive evaluation of machine learning-based earthquake prediction and identify areas for improvement [32].

To improve earthquake prediction, scientists combine geological studies with machine learning, specifically the random forest algorithm, to make short-term predictions based on past events. They propose a hybrid model that combines geological and machine learning techniques to improve accuracy. New methods of using seismic acoustic data to train learning models to predict future earthquakes provide hope for earthquake research and mitigation of the impact of seismic events [33]. The researchers aimed to develop a reliable prediction model using earthquake location data and the Japan Meteorological Agency (JMA) dataset. Using SMOTE to resolve inconsistent data and measure performance, they achieved an accuracy of 97.77%. Although there are limitations in predicting large earthquakes and overestimating small earthquakes, the model is promising for the early detection of earthquakes (EEW), which is important for providing information during seismic events [34]. These studies focus on improving the accuracy of hydroacoustic signal estimation, which is important for noise reduction and signal processing. The hybrid model includes VMD, DE, ELM, SVR, and ABC optimization to improve power prediction compared to existing methods. It solves the fusion problem, improves accuracy, and provides useful hydroacoustic group estimation [35].

This study developed a Ground Surface Prediction (GMPE) model for India using XGBoost machine learning. The model was run on seismic data using parameters such as time, distance, depth, and seismic shear wave velocity and Bhuj aftershock data obtained a good correlation (±0.994) between observed and predicted PGA values, indicating the suitability of various seismic parameters. has shown [36]. This study investigates the impact of seismicity signals on earthquake prediction in four regions of Chile, focusing on training/testing, b-value calculation, and product transformation. Accurate measurements and appropriate length selection increase prediction accuracy and highlight the importance of supervised learning algorithms in seismic data analysis. Multifunctional designs support a variety of uses, emphasizing the importance of these aspects in improving earthquake prediction [37]. The research focuses on improving early earthquake warning (EEW) through machine learning-based damage prediction immediately after the arrival of long waves. The current system is based on low movement of the ground, which creates uncertainty in decision-making and leads to a lot of financial losses. The proposed method uses long-wave characteristics to predict the maximum interlayer drift ratio (MIDR) and achieves a prediction accuracy of over 96.4%, ensuring stability and efficiency for EEW systems [38].

In earthquake research, scientists use deep learning to improve location estimation without making any prior decisions about fault information. This neural network passes classical methods such as the Coulomb failure stress function with AUCs of 0.849 and 0.583, respectively. The model improves seismic damage location prediction by combining physical properties such as stress transfer and von Mises effect, demonstrating machine learning capability in seismic safety assessment and understanding earthquake dynamics [39].

Scientists in the Horn of Africa are using deep learning to try to improve earthquake predictions by adapting to variables that change over time. They compared Transformer, short-term memory (LSTM), bidirectional long-term memory (BILSTM), and BILSTM-AT models and found that Transformer outperformed other models with 0.276 MAE, 0.147 MSE, 0.383 RMSE, and 28.868% MAPE, respectively. potential for disaster planning [40]. To improve the understanding of underwater propagation, researchers used CRAN to integrate convolutional autoencoders and LSTM-based recurrent neural networks. By training on different seamount geometries and acoustic wave frequencies, CRAN predicts wave propagation up to 5-6 times the initial length, demonstrating the power of deep neural networks in searching for physics. This architecture should enable real ocean applications and improve many wave physics studies [41]. To solve the earthquake problem, research goes beyond the traditional method and uses LSTM networks to capture the relationship between body and body. LSTM networks with two-dimensional features improve the accuracy of predictions by using historical data over a larger area. Simulation results showed very good prediction ability, demonstrating the potential of deep learning and highlighting the importance of location and physical structure in earthquake prediction [42].

In seismic data analysis, researchers evaluated the effectiveness of ANN in earthquake prediction based on support vector machine (SVM), M5P, Naive Bayes, KNN, J48, random forest, and LPBoost ensemble method. It is worth noting that non-magnetic materials produce good results in active regions such as Chile, Japan, India, China, Pakistan, the United States, the Iberian Peninsula, Greece, and Portugal, encouraging future studies to address the problem of simultaneous prediction. . to improve accuracy [43] This experiment uses features such as event time, latitude, longitude, depth, and size to evaluate the ability of artificial neural networks (ANNs) to predict large earthquakes. Demonstrates the performance and information of the model using USGS and ISIDE datasets, achieving a 10% error in estimating size and performance data. Despite the limitations of the ISIDE dataset, the neural network can predict small (M-2.0) events with 99% accuracy and accurately predict medium-sized events (2.0 allowing us to see the power of AI in supporting global seismic data. . Daily seismic forecast potential [44]. This paper presents an artificial neural network (ANN) to determine the probability of arrival time (IAT) of seismic events in six seismic zones of India. The inadequacy of classical methods due to the complexity and heterogeneity of the data leads to the emergence of ANN-based methods that perform better than classification models. The ANN method accurately predicts the IAT result, aids in loss prediction, recovery, operational planning, and application design, and provides a powerful modeling tool for seismic data acquisition.

The researchers aimed to create a tsunami travel time (TTT) atlas that could be used to estimate the time of arrival (ETA) of tsunamis caused by various earthquakes, especially ins the Indian Ocean. This study uses non-standard electronic equipment for ETA estimation due to its speed and consistency. The TTT atlas was launched on the anniversary of the Indian Ocean tsunami to provide coastal communities with important information on disaster preparedness. This study highlights the importance of integrating new technologies into early warning systems to improve disaster risk reduction [46]. In pharmaceutical research, artificial neural networks are successful in revealing non-linear relationships between various properties, providing efficiency and balancing ability. This chapter provides an overview of the development of ANNs, explaining the basic concepts and their advanced applications in pharmaceutical research. The impact of network learning and configuration on the performance and performance of neural network devices is briefly discussed [47].

In-depth analysis of severe tsunamis and economic impacts, particularly in Taiwan, using deep learning to reveal historical data. In particular, features obtained from images from the last 120 days have an R-value of 0.303 for predicting earthquakes above magnitude 6 within 30 days, revealing the potential for automatic prediction of seismic zones [48]. Researchers used RNN to analyze the earthquake in Turkey's Dizce province by combining various factors such as the earthquake's magnitude, depth, moon-to-ground, b-value, and d-value. By combining seismic coefficients and lunar data, prediction accuracy can be increased and the impact of seismic events can be reduced. Although there are problems due to inaccuracies in seismic data, many RNN models show promise in earthquake prediction and may aid future research [49]. In 1994, a new earthquake prediction method that incorporated financial analysis tools into neural networks predicted the Azores earthquakes of July 1998 and January 2004 at different times and locations. By combining physical precursors and computational oscillators, the network is trained to predict future events in the population over a long period. Promoting key benefits within the improvement domain [50].

Researchers investigated multilayer perceptron (MLP) neural networks for earthquake prediction and evaluated 128 seismic data samples. The prediction accuracy of online training reaches 72%, which is slightly better than mass training. A short run time increases the probability of amplitude estimation. Online models M16208 and M16204 produced the best predictions, demonstrating the effectiveness of MLP in predicting large earthquakes without prior assumptions [51]. The proposed DIN-MLP algorithm integrates MLP and DIN models to solve data processing problems in non-seismic situations and improve prediction accuracy by monitoring field behavior. Seismic monitoring stations are considered special users and historical data models are used as recommended products. Comparative tests show that GAUC increases by 11% over the original DIN model, demonstrating the effectiveness of estimating missing seismic data. The practical application of seismic monitoring centers aims to increase efficiency and accuracy, and future research focuses on standardization and optimization [52].

This paper presents a new method to predict the timing of major earthquakes in Hormozgan Province using the RBF neural network (NN) model. Input vectors include seismicity values ​​for large events and are optimized for training with limited data. Reasenberg's traditional methods increase data integrity. The results show that the RBF model outperforms MLP NN in terms of accuracy, cost, and precision; this highlights the importance of seismic data assimilation and the effectiveness of RBF NN in reducing the time correlation of seismic risk in the region [53]. This paper presents the IABC algorithm, which improves the MLP neural network for earthquake time estimation and overcomes backpropagation limitations. Compared to BP-MLP, IABC-MLP is more accurate, especially in predicting larger earthquakes. The advantage of weighted values ​​of the IABC algorithm improves learning and provides a good way to improve MLP training in earthquake prediction [54].

This article provides an overview of global tsunami-induced science and discusses tsunami characteristics, causes, and effects on coastal sedimentation and topography. It provides an in-depth study of hydrological and morphodynamic numerical models used to simulate tsunami and sedimentation processes in terms of collaborative research and development of hazard assessment strategies for each region [55]. The growth of subcritical cracks in solids with low stresses and strains generally results in a slow and steady propagation equal to the maximum compressive stress. This creates a positive seismic anisotropy that facilitates earthquake prediction by dilatational anisotropy (EDA). This system detects earthquakes by estimating the distance to the next epicenter, interpreting the split wave analysis as pre-earthquake stress analysis [56].

This research explores ways to improve tsunami warnings using new technologies. It is recommended to use our tools: tsunami forecasts, flood maps, and port flow maps. These will assist in evacuation, port control, and rescue. Public education is also considered important. Research suggests better warning systems and education to make coastal communities more resilient to tsunamis [57]. Earthquakes occur when energy measured by seismometers is suddenly released below the Earth's surface. Small earthquakes occur every day around the world, but most of the time they are undetectable and harmless. China, Indonesia, and Japan are at risk of earthquakes due to plate movement, human activities, and fires. Monitoring seismic activity helps reduce the risk to human life and the environment [58]. This study highlights the importance of real-time data from marine observatories, especially in Japan, for earthquake and tsunami monitoring. These observations developed by JAMSTEC aid in earthquake detection, damage mitigation, and advanced understanding of coastal seismicity, boundary deformation mechanisms, and tsunami early warning systems and speak to the need for advancement in coastal earthquake monitoring [59].

This research improves traditional tsunami models by ignoring fundamental issues such as sea level changes and acoustic effects. It uses advanced techniques to perform simulations without these simplifications, revealing larger wave heights and significant arrival times varying close to the error. The combination of seafloor dynamics and acoustic disturbances can improve the accuracy and understanding of tsunami behavior [60]. This study investigates acoustic gravity wave measurements as potential tsunami precursors. To evaluate early tsunami detection, he used two-dimensional linear theory to analyze the electrical parameters generated by the displacement of a piston incompressible water. Findings show that great pressure was recorded on the coast before the tsunami, and studies are continuing to solve the constraints and provide analysis of three-dimensional problems using Mathieu functions [61]. Geller et al. The dispute over the reliability of earthquake predictions is based on the occurrence of unexpected and unpredictable events in the world. They highlight the complexity of seismic activity, acknowledging that even small earthquakes can lead to larger events. Disagreement continues over evaluation and media coverage. In general, they believe that accurate earthquake prediction is impossible [62].

Seismic activity in the Indian Ocean, especially in the northeast, occurs at ocean ridges and rift valleys. There were 29 earthquakes in the region, 11 of which were magnitude 6 or greater, especially in the coastal areas of Irvine, Prince Edward Island, and Amsterdam. The equation obtained from 30 years of data shows that the earthquake frequency decreases logarithmically with magnitude, with 6 and 8 earthquakes occurring every 6 and 50 years, respectively [63]. This study develops a method for instantaneous prediction of severe tsunami wave height and coastal flooding, focusing on the impact of the 2004 Indian Ocean tsunami in Cuddalore, India. This study uses the ADCIRC model to accurately calculate wave height and sea level, which are important for emergency warnings and disaster planning decisions. This highlights the importance of timely and accurate forecasts to reduce the impact of tsunamis on coastal communities [64].

This report evaluates the economic impact of the 2004 Indian Ocean tsunami in Indonesia (Aceh Province) and Sri Lanka on the coastal environment in terms of disaster preparedness and environmental management. It advocates integrating disaster risk reduction into national development strategies and emphasizes the importance of community participation and program management to achieve good outcomes. [65].

The Indian Ocean tsunami caused by the major earthquake in 2004 demonstrates the lack of planning and early warning in the region. Advances in seismology and tsunami science have improved earthquake warning, prediction, and paleoseismological research. Improved tsunami modeling, GPS buoys, and improved propagation models have led to early warning systems, hazard maps, and risk assessments. Collaboration between scientists and stakeholders is essential for disaster mitigation through a deeper understanding of events such as the 2011 Tohoku earthquake and the collision at the Fukushima Daiichi nuclear power plant [66].

Scientists use seafloor-distributed acoustic sensing (DAS) and fiber optics for tsunami warnings. Data collected at 100 Hz, and 20 m intervals, were analyzed using FK beamforming. Following tsunami predictions, ships that could survive for more than 300 seconds were detected. Gravitational waves (200-600 seconds) are consistent with DART data. DAS improves detection capabilities and aids coastal planning, but further research is needed [67]. To improve the prediction of tsunamis after a large ocean earthquake (M > 7), researchers analyzed the fault location, magnitude, fault direction, and earthquake characteristics. Signal analysis techniques such as Fast Fourier Transform (FFT) and Continuous Wavelet Transform (CWT) of time-lapse data can distinguish tsunamis from non-tsunami earthquakes, thus improving the accuracy of prediction and timely warning [68].

Earthquake history in the Caribbean, Indonesia, and Japan is difficult to track and document. Despite their geographical differences, Indonesia and the Caribbean, two large archipelagos, share similar seismic activity patterns and atmospheric patterns. This 35-year study since 1985 investigated the link between climate science and seismic anomalies by using precipitation patterns to identify earthquake zones in various ocean regions [69].

The author proposed a method to predict earthquakes and tsunamis by measuring elastic waves and radio waves in the seismic zone, and the highest measurement results were 0.95. Electronic devices with frequencies between 1 Hz and 1000 Hz can detect earthquakes and measure the severity of the electric shock that causes elastic ruptures. The global research target is planned to be completed within 4-5 years [70]. The study examined acoustic gravity waves as potential tsunami precursors and examined electrical waves produced by the displacement of the bottom of a piston in the ocean. It describes the flow of water using discharge theory and demonstrates early detection of the tsunami by pressure signature. Future research is to use acoustic measurements to resolve tsunami forecast inversion by accounting for factors such as energy loss and bottom irregularities [71]. To improve the prediction of earthquake deaths, researchers evaluated the significance of various earthquakes in Yunnan Province. They use key challenges such as identification and downscaling to determine important factors such as population distribution and geohazards. Particle swarm optimization support vector machine achieves high accuracy (R2 higher than 0.934) by improving the accuracy of machine learning models for earthquake emergencies and post-disaster reconstruction [72].

Examining earthquake patterns before and after main shocks in the south and north Researchers in California and Italy have developed a foreshock test. When they compared observed foreshocks to ETAS model simulations, they found more visible foreshocks that tell the difference between aftershocks. This means that changes in the body system before the main shock will improve the prediction of large earthquakes [73]. This study examines the time of the wave train T(Q) at teleseismic distance from stations on the island, including seismic factors (mb, Ms, Mw). He analyzed data from more than 400 Pacific earthquakes using theoretical models and measured the logarithmic relationship between time and earthquake magnitude. The results confirm the prediction, especially for large earthquakes (Mw > 7) and help predict the very long seismic period of 1 to 2 hours after the earthquake. These models provide immediate and accurate estimates of earthquake duration and are important for effective tsunami warning [74].

**Methodology**

**References**

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