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Article Title: **An Ai-Driven Tsunami Prediction Framework Using Chicken Swarm Optimized Artificial Neural Network**

An Ai-Driven Tsunami Prediction Framework Using Chicken Swarm Optimized Artificial Neural Network

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ABSTRACT

Tsunami detection in the coastal area is a major problem and a big impact on the environment, therefore early detection and training for tsunami need to be carried out to reduce the impact of casualties and losses incurred. Machine learning techniques, with their ability to identify patterns and anomalies, offer an approach for tsunami detection. This paper introduces a novel tsunami detection model combining the Chicken Swarm Optimization (CSO) Algorithm and Artificial Neural Network (ANN) classifier. Using the data pre-processing technique such as data cleaning and data visualization the input dataset is processed and featured using speedup data transformation the raw data is converted in to certain data using feature engineering. This hybrid approach effectively analyses the detection of tsunami by leveraging the strengths of both methods. The model is trained and evaluated using the earthquake dataset, achieving a commendable accuracy of 92%. The software used here is python. The proposed model demonstrates superior results compared to existing techniques, offering an efficient solution for environment.

Keywords: Tsunami detection, data cleaning, data visualization, speedup data transformation, Chicken Swarm Optimization (CSO), Artificial Neural Network (ANN).

1 Introduction

Natural disasters are incidences caused by natural processes that are harm to everyone in the world [1]. Tsunami is one of the types of natural disaster that causes a lot of damage. When tsunami strikes an area, it causes disorder and falloff a variety of effects [2]. However tsunami is a catastrophic effect on both human life and the economy. In recent year's tsunami have become more frequent with a overall of 251,770 fatalities and USD 280 billion in harms among 1998 and 2017. Because of this, among other things, Tsunami Early Warning Systems (TEWS) is crucial to catch the location [3]. One early detection technique that can reduce the impact of losses and casualties is tsunami prediction. [4]. In fact, tsunamis are identified, and warnings are sent based on information about earthquakes, such as the hypocenter's position and magnitude. The primary source of tsunami warnings is real-time seismic stations, which track underwater seismic activity using earthquake data such focal depth, magnitude, time of origin, and epicenter to rescues the people [5]. Moreover, creating efficient rescue strategies and avoiding cascading effects depend on precisely gathering data regarding the dynamic evolution of disastrous events [6].

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The application of Machine Learning (ML) techniques is rapidly expanding and active in all areas of research, including tsunami science. However to analyse land use and tsunami vulnerability a Random Forest (RF) classifier is used to detect the tsunami waves [8]. Additionally, logistic regression is used to categorize earthquakes that produced tsunamis using characteristics related to the size and depth of the earthquake. When tsunami arose it provides warning message to the tsunami warning agencies [9]. Then a Decision Tree (DT) algorithm are used here to make tsunami predictions based on the set of variables, the combination of the maximum flow velocity and critical flow depth [10]. Consequently, TEWS use the regression tree technique to predict the maximum height of incident waves at specific target points in front of the coast. This allows early warnings message to areas where a tsunami waves are destructed and to deliver an immediate impact on the area [11].

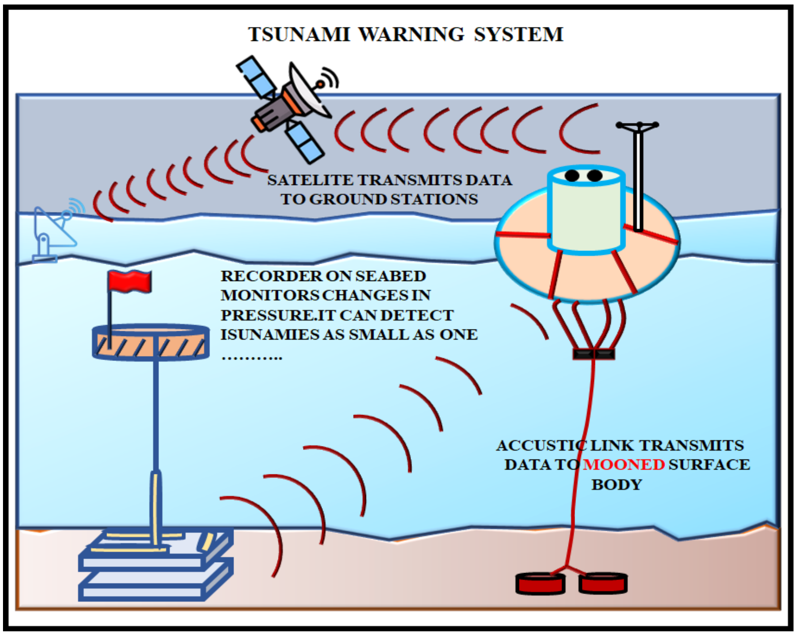

Figure 1: *Tsunami Warning System*

Deep learning-based tsunami prediction models are used to forecast tsunami waves. Here the tsunami wave is predicted using Convolutional Neural Networks–Long Short-Term Memory (CNN–LSTM) and Bidirectional Long Short-Term Memory (Bi-LSTM) models. However, using the same input–output ratio, more inputs are not prediction successfully [12]. Next, by training a Multi-Layer Perceptron (MLP) network over a broader area, the tsunami Estimated Time of Arrival (ETA) on a restricted location is determined to find the tsunami wave. The network architecture uses a database of predicted ETAs as input. However it shows only one hidden layer with ten hidden neurons are resulted [13]. Additionally, convolutional neural networks for assessing Coastal hazard by video Analysis (LEUCOTEA) are a monitoring system that evaluates storm, wave, and tide data from a video recording [14]. In additional, coastal tsunami prediction utilizing a Denoising Auto Encoder (DAE) model based on S-net observations is used and the drawback is it is predicted 15minutes after the earthquake [15]. To overcome the limitations, the developed work introduces CSO optimized ANN to find the tsunami detection using earthquake dataset that enhances the network performance of the deep learning-based neural network. The deep neural networks have higher proficiency in handling large data and they are more trained in classification techniques.

2 Related work

Dharmawan *et al* (2024) [16] have proposed a Recurrent Neural Network (RNN) on tides prediction for tsunami detection in the coastal area. Here to solve tide prediction in shallow water cases a multistage pre-processing and RNN-based deep-neural network is processed. In shallow water cases it reduce the noise of the tides data and accommodate the neural networks as output here the tsunami is predicted. The drawback is it is difficult to train the network.

Núñez *et al* (2022) [17] have developed a DL-method called 1Dimensional- Convolutional Neural Network (1D-CNN) used to find the tsunami time series. A 1D-CNN is used to anticipate wave time series at specific location and displays the time series least number of false alerts or missed alarms. The disadvantage is that it requires a lot of labelled data to train adequately.

de la Asunción, M. (2024) [18] have proposed a deep learning method called Multi-Layer Perceptron (MLP) neural networks for predicting the alert level due to a tidal wave at given coastal locations. This type of simulation is accelerated by contemporary Graphics Processing Units (GPUs), but it still takes a lot of minutes or even hours for models and that need to handle with extremely high spatial resolutions. With the MLP approach, it is also possible to forecast the alarm or inundation level of a tsunami caused by an earthquake. The weakness is computational expense and complexity.

Rim *et al* (2022) [19] have invented a Convolutional Neural Network to predict tsunami waveforms based on Global Navigation Satellite System (GNSS) data for hypothetical earthquakes. CNN first applies a sequence of nine pairs of convolutional and max-pool layers, and then applies the 8 transposed convolutional layers to predict the tsunami waves. The problem is it takes more time to predict the wave forms nearly six hours.

Makinoshima *et al* (2021) [20] have proposed a Convolutional Neural Network for early warning of tsunami prediction. To predict tsunami a numerical tsunami forecasting tests are used for the performance with average maximum amplitude and tsunami arrival time to forecast the errors. Here, a single CPU node is used to capture the wave's projected amplitude and duration. The disadvantage is difficulty in obtaining and annotating.

3 Proposed work

The proposed block diagram for tsunami prediction using machine learning technique is applied to earthquake datasets. The data’s are collected as a raw data which includes seismic activities, underwater earthquakes, tectonic plate shifts, and other oceanographic factors are gathered from monitoring stations, satellites, and historical records. At first the input data is processed using the data pre-processing stage that includes cleaning the input data by handling missing values, removing outliers, and normalizing. Also, to analyze patterns, such as the relationship between underwater seismic events and tsunami occurrences, to gain insights into critical trends a data visualization method is used. Then the processed data is given as the input to feature engineering here earthquake magnitude, depth, location, ocean floor deformation, and water column displacement related to tsunami prediction are extracted. At last model training is transformed and optimized using the featured data.

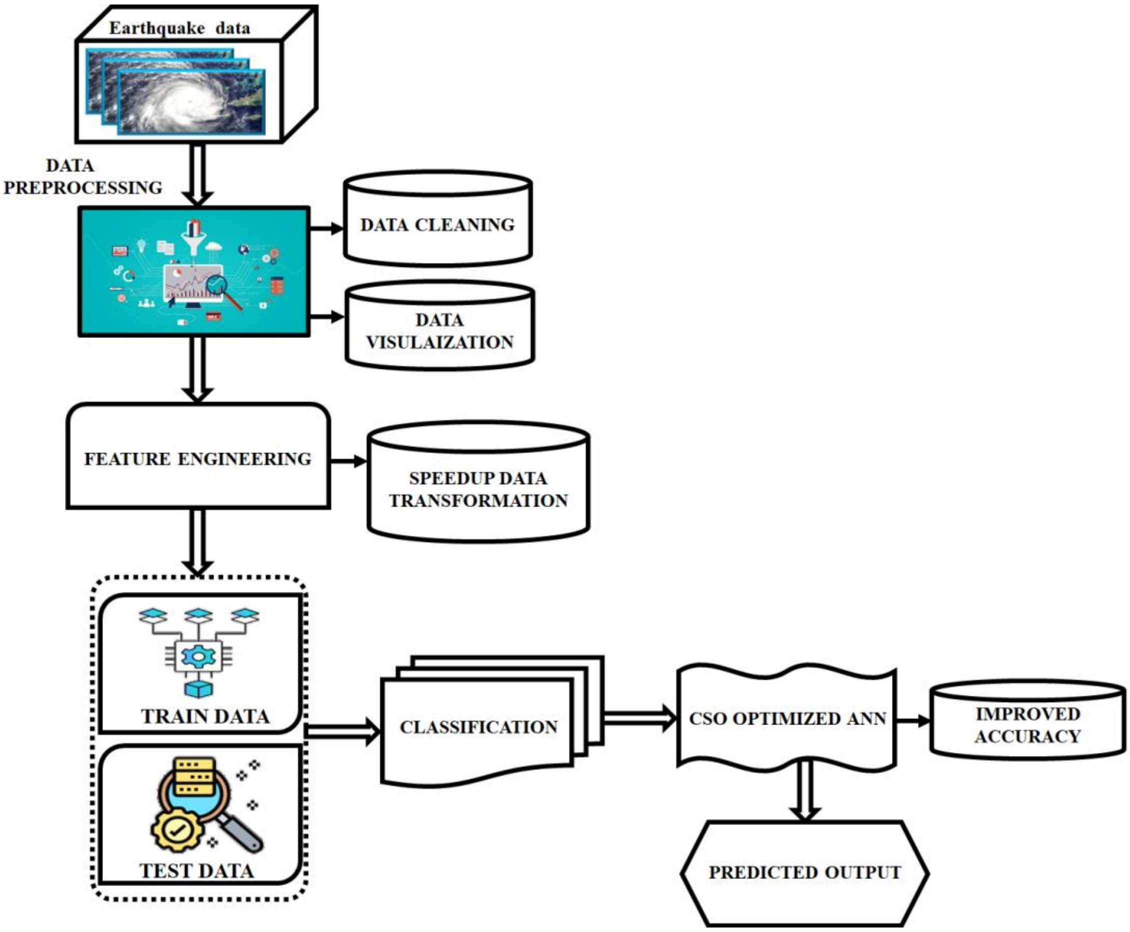

Figure 2: *Proposed block diagram of CSO optimized ANN*

To evaluate the model's accuracy and generalizability the dataset is split into training and testing data. In classification stage, a Chicken Swarm Optimization optimized Artificial Neural Network (ANN) is utilized to increase the accuracy and efficiency. To improve model accuracy, faster convergence, and reliable predictions of tsunami events the optimization technique is used. In order to minimize the impact of tsunamis on coastal regions, the model finally generates the predicted output, which offers useful information for disaster management and tsunami early warning systems. This process combines domain-specific knowledge with advanced machine learning techniques to increase the reliability of tsunami prediction systems.

3.1 Data Pre-processing for tsunami detection

The first step in the data pre-processing is data cleaning and data visualization for tsunami detection.

3.1.1 Data cleaning for tsunami detection

The process of eliminating or correcting corrupted, incorrect, duplicate, from datasets is known as data cleaning in earthquake dataset. Cleaning up the dataset is the primary objective in order to standardize data analysis and make it easier to locate the right earthquake data for a query. Duplicate data observation occurs during dataset collection.

3.1.2 Data visualization for tsunami detection

To analyse patterns, such as the relationship between underwater seismic events and tsunami occurrences, to advance visions into critical movements a data visualization method in earthquake dataset. A control window allows you to choose which site to visualize on the map of the inundation area. Now the lists of arrival timings and heights are also displayed, along with bar graphs of real-time pressure gauges and calculate the waveforms for the expected point that depict the tsunami's propagation. The forecast is initiated when the seafloor observatories identify the triggering of a tsunami. If the tsunami is coming from a nearby area, the inundation area is expanded. The model distribution in the earthquake database determines the time gap between subsequent forecasts on the display, but the prediction data is generated at one-second intervals. Next to data pre-processing stage the input earthquake data is given to the feature engineering.

3.2 Feature engineering for tsunami detection

Feature engineering is the second stage here the pre-processed data is used as the input to feature using speedup data transformation.

Speedup data transformation for tsunami detection

In feature engineering step the data is speedup by transforming the raw earthquake data into a certain format is known as data transformation process and it possible to extract the strategic elements more quickly and effectively. The raw earthquake dataset is converted into the proper format before the information is retrieved because it is hard to track and comprehend. The data transformation process is essential to produce comprehensible patterns since it facilitates the strategy involved in data conversion. Techniques like smoothing, aggregation, and generalization are used in data transformation to change the data into a specific format. The process of smoothing is used to eliminate noise from the earthquake dataset. Then by the feature engineering stage input earthquake data is given to the data splitting.

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3.3 Data splitting for tsunami detection

Data splitting involves dividing the earthquake dataset into training and testing sets. The ML algorithm is trained on the training set, and the model's performance is assessed on the testing set. However, the earthquake data is splitting as 80 trained and 20 testing samples. When the testing subset is altered, the earthquake dataset loses its validity. Next by data splitting the earthquake data is given to the proposed CSO optimized ANN technique.

3.4 Classification for tsunami detection

In this proposed work the proposed Deep Learning method called CSO optimized ANN is utilized for effective detection of tsunami. An artificial neural network is trained and chicken swarm optimization is a meta-heuristic that mimics the hierarchical order, foraging, and learning behaviours observed in chickens.

Artificial Neural Network for tsunami detection

As seen in Figure, an artificial neural network will be utilized to model the featured earthquake data. The ANN design of the earthquake data utilized in Figure is based on input parameters and includes input layers, hidden layers, and an output that represents the occurrence of tsunamis. An artificial neural network is then used to model the training data. Because the Artificial Neural Network model uses activation to link layers and provide an output. Feed-forward neural networks (FFNNs) are clusters of numerous perceptron's at each layer that sift input data in a forward direction.

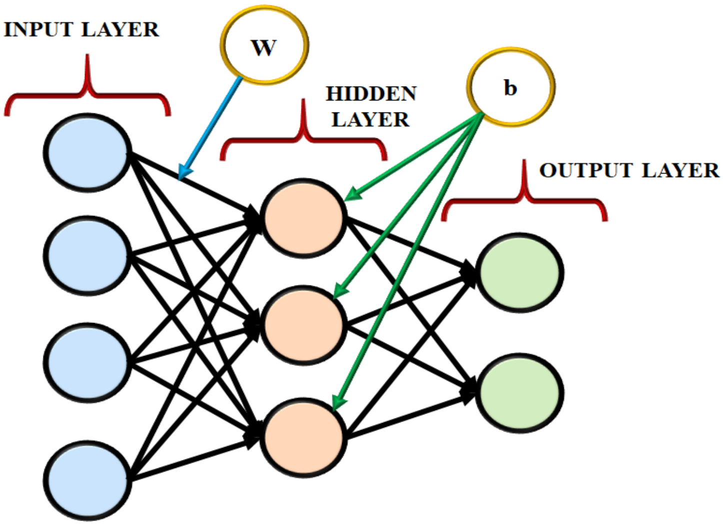

Figure 3: *Artificial Neural Network*

The input layer receives the earthquake data, which is then computed by the hidden layers and results are provided by the output layer. In neural networks, each layer's duty is to learn particular decimal weights that resolve the learning process. The parameters of ANN classifier is optimized using CSO algorithm.

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Chicken Swarm Optimization for tsunami detection

To improve the accuracy of the ANN technique this work examines and explores the Chicken Swarm Optimization (CSO) algorithm, an exciting bio-inspired algorithm that is based on what way a hens, chicks, and cocks hunt food. For the entire chicken swarm, 3 different kinds of chicken are used: hens swarm, chicks swarm, and cocks swarm. In the CSO algorithm, each role have a dissimilar weight; for example, cock swarms have the uppermost fitness and chick swarms have the lowermost fitness according to the algorithm. During algorithm execution, the roles (hen, chick, and cock) are assigned based on the algorithm's fitness value. The goal of the CSO algorithm is to minimize errors in any control problem.
The individuals in each subgroup are separated into three levels: hens, chicks, and roosters. The proportions of hens, chicks, and roosters are $N_r, N_h \& N_c$ respectively. The position of the i^{th}chicken in the k^{th} iteration of the j −dimensional search space is represented by the algorithms$x_{i,j}^{t}$. The roosters are chosen from among the individuals with the lowest fitness value. Equation (1) illustrates how the position of the roosters is updated as they move randomly over the search space.

$$x_{i,j}^{t+1} = x_{i,j}^{t} * (1 + randn(0, \sigma^2)) \quad (1)$$

Where, $randn$is a random number with a Gaussian distribution$(0, \sigma^2)$. Individuals with more fit are chosen to be hens, which follow the rooster. Equation (2) illustrates how the hen's position is updated.

$$x_{i,j}^{t+1} = x_{i,j}^{t} + S_1 * rand * \left(x_{r1,j}^{t} - x_{i,j}^{t}\right) + S_2 * rand * ((x_{r2,j}^{t} - x_{i,j}^{t}) \quad (2)$$

Where the i^{th} hen comes after the individual rooster are denoted by r_1. A randomly selected roaster is $r_2$chosen or hen$(r_2 \neq r_1)$. Weights $S_1 = \exp((f_i - f_{r1})/(abs(f_i) + \varepsilon))$ and $S_1 = \exp((f_{r2} - f_i)$should be determined. The fitness values $f_{r1} \& f_{r2}$ are equivalent tor_1 &r_2, respectively.
Other individuals are classified as chicks, with the exception of hens and roosters. Equation (3) illustrates how the chicks follow their mother's movements and adjust their position accordingly.

$$x_{i,j}^{t+1} = x_{i,j}^{t} + FL * \left(x_{m,j}^{t} - x_{i,j}^{t}\right) \quad (3)$$

Where $FL \in [0,2]$, $\left(x_{m,j}^{t}\right)$ is the i^{th} mother chick's position. ANN is the technique to predict tsunami occurrences and it is optimized by the CSO algorithm to reduce the error and thus improve the accuracy of the ANN model.

4 Result and Discussion

The suggested detection model categorizes earthquake dataset for tsunami detection in five countries they are Solomon Islands, Papua New Guinea, Indonesia, Vanuatu and Chile.

Furthermore, testing in Python applications helps to understand the detection model's capabilities.

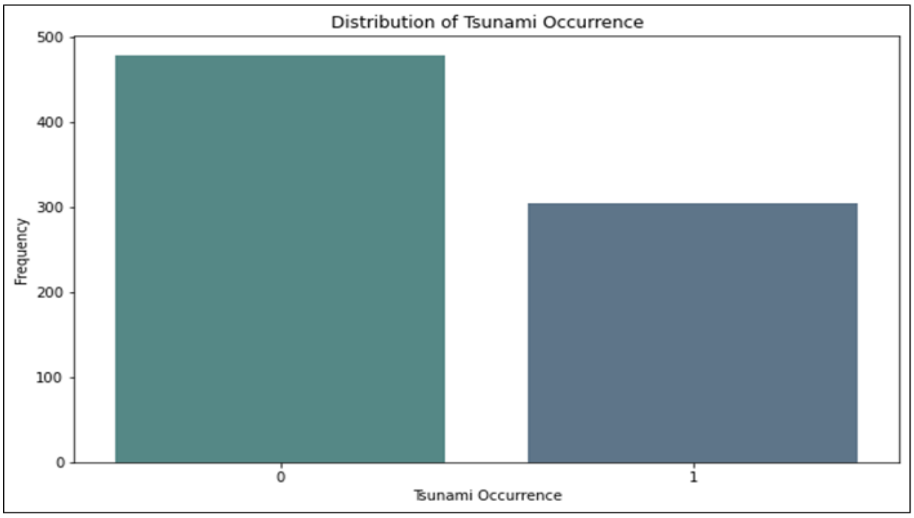

Figure 4: *Distribution of tsunami occurrence*

In above figure 4 the distribution of tsunami occurrence with frequency is mentioned. Here 0 indicates there is no tsunami and 1 indicates there is a presence of tsunami. The frequency ranges from 0 to 500. For 0 indices range from 0 to 480 and 1 indices ranges from 0 to 300.

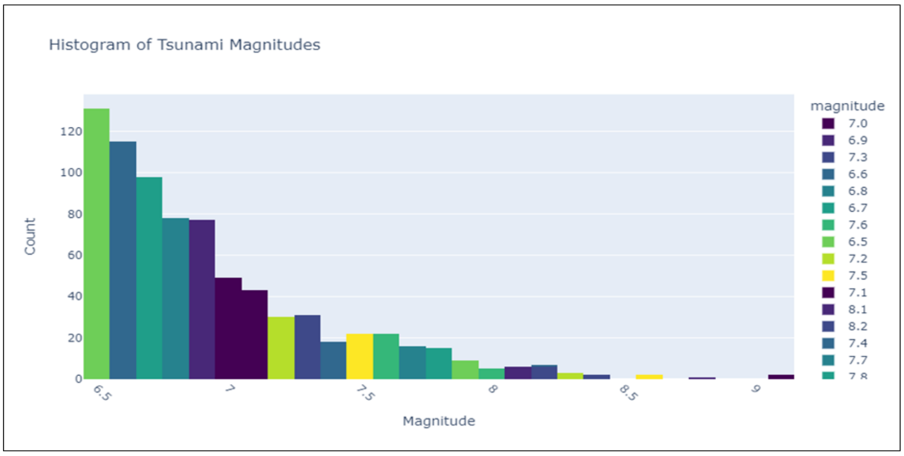

Figure 5: *Histogram of tsunami magnitudes*

The histogram of figure 5 illustrates the distribution of tsunami magnitudes, categorized by magnitude ranges. The majority of tsunami occur within the lower magnitude range of 6.5 to 7.0, with the frequency decreasing as the magnitude increases. Higher magnitude tsunami above 8.0 are relatively rare. This visualization highlights the prevalence of low to moderate-magnitude tsunamis in the dataset.

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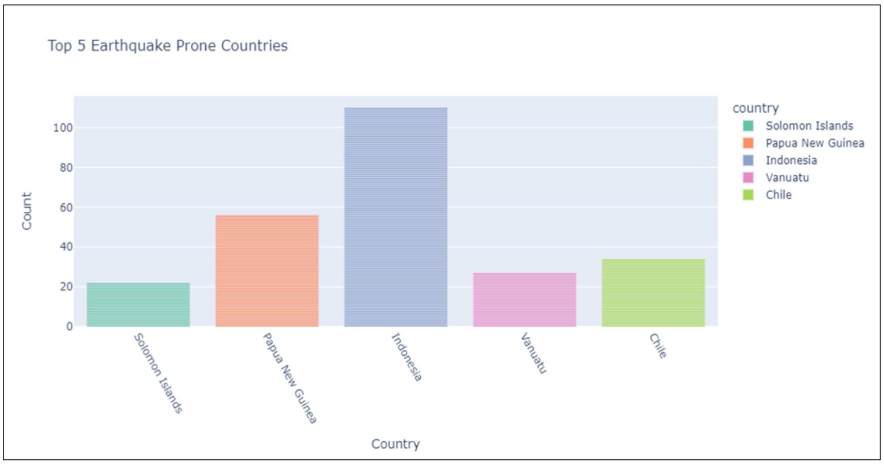

Figure 6: *Top 5 earthquake-prone countries*

The bar chart of figure 6 shows the top five earthquake-prone countries based on the count of recorded earthquake events. Indonesia experiences the highest number of earthquakes, followed by Papua New Guinea. Chile, Vanuatu, and the Solomon Islands also rank among the most affected countries, though with relatively fewer events compared to Indonesia. This highlights Indonesia's vulnerability to seismic activity.

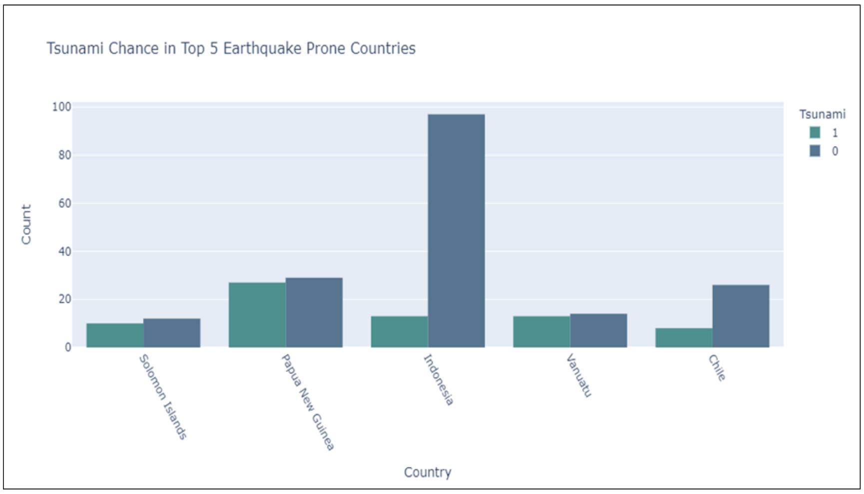

Figure 7: *Top 5 earthquake-prone countries*

The bar chart in figure 7 depicts the likelihood of tsunamis occurring in the top five earthquake-prone countries. Indonesia shows the highest count of earthquake events linked to tsunamis, while other countries, such as Papua New Guinea, Chile, Solomon Islands, and Vanuatu, have lower occurrences of tsunami-triggering earthquakes. This emphasizes Indonesia's heightened vulnerability to tsunamis due to its frequent seismic activity.

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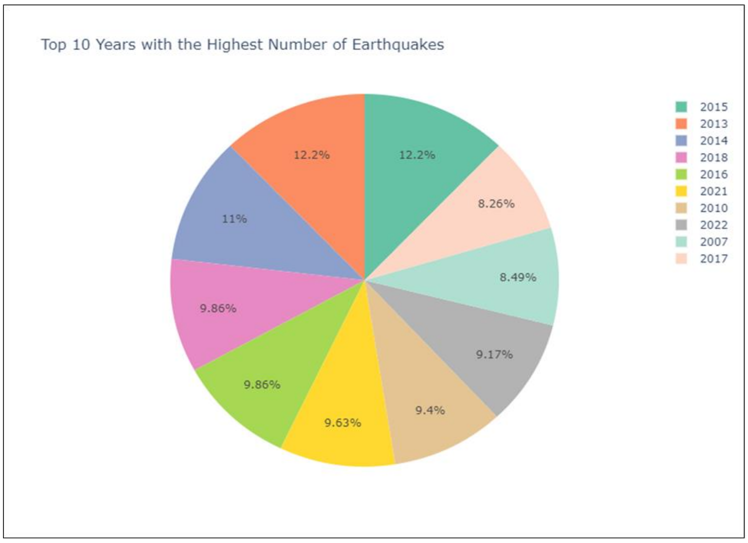

Figure 8: *Top 10 years with the highest number of earthquake*

In the above figure 8 the highest number of earthquakes are measured for past 10 years, here it is peak in 2013 and 2015 it is about 12.5%, in 2014 it is about 11%, in 2016 1nd 208 it is about 9.86%, in 2021 it is about 9.63%, in 2010 it is about 9.45, in 2022 it is about 9.17%, in 2007 it is about 8.49% and low in 2017 it is about 8.26%.

Top 10 Countries with Highest Tsunami Probability

Country	Tsunami Probability (%)	Total Earthquakes
13	88.89	9
11	66.67	6
36	58.82	17
29	55.56	9
49	50.34	298
40	50	6
33	48.21	56
47	48.15	27
38	45.45	22
24	45	20

Figure 9: *Top 10 countries with the highest probability of tsunamis*

The table in figure 9 displays the top 10 countries with the highest probability of tsunamis, calculated as the percentage of tsunami-triggered events out of the total number of earthquakes recorded in each country. The country ranked highest takes an 88.89% tsunami probability based on nine earthquakes, while the rest show probabilities ranging from 66.67% to 45%, with varying total earthquake counts. This highlights regions with a higher likelihood of tsunamis following seismic events, emphasizing the need for targeted disaster preparedness and mitigation efforts in these areas.

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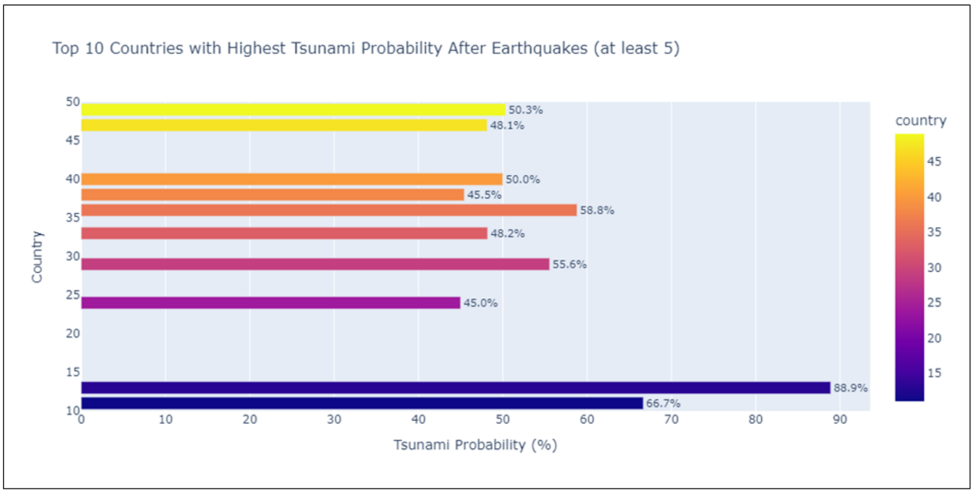

Figure 10: *Top 10 countries with highest tsunami probability after earthquake (at least 5)*

In the above figure 10 the top 10 countries with highest tsunami probability after earthquake (at least 5) is captured. It is very high in the country 13 with the probability of 88.9% and in country 10 it is about 66.7%.

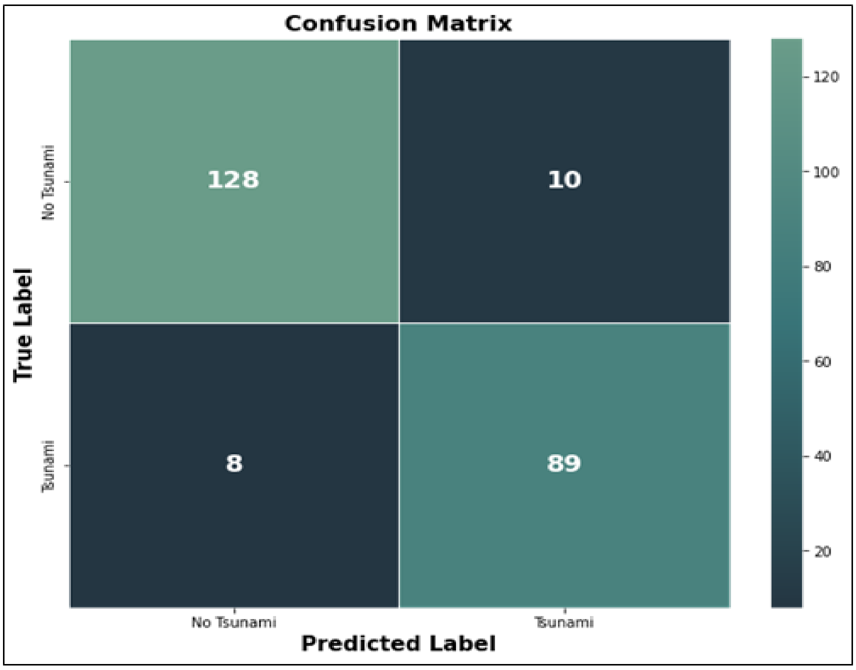

Figure 11: *Confusion matrix for tsunami detection*

Figure 11 illustrates the confusion matrix for CSO optimized ANN for tsunami detection. This matrix shows the values for true and predicted labels. Confusion matrices are commonly utilized to evaluate the performance of classification models, particularly those tasked with predicting categorical labels for input instances.

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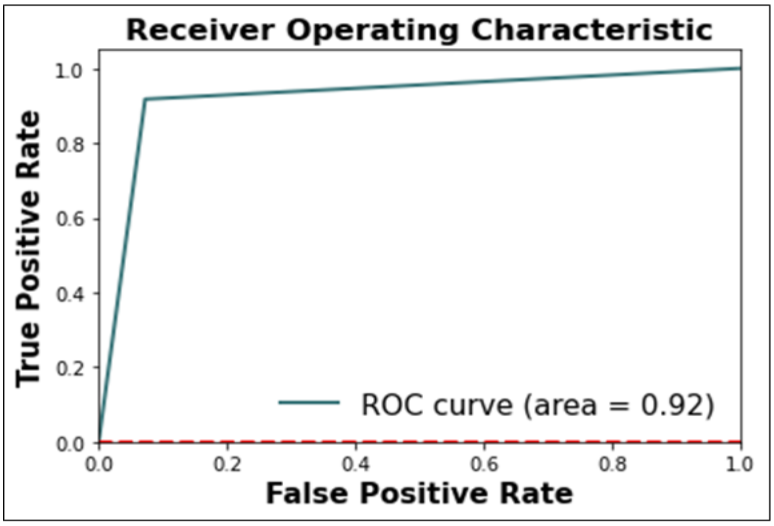

Figure 12: *ROC curve for tsunami detection*

According to the results shown in Figure 12, the earthquake, the suggested CSO optimized ANN continues to have the highest AUC value of 0.92, demonstrating the unique overview and flexibility of this approach.

Comparison for the proposed method

In contrast, several other studies [10, 15] depend on baseline data, ignoring the training data's time series component. These studies did not sufficiently explain their findings and lacked training data for detection analysis in table 1.

Table 1: *Comparison for the proposed method*

Study	Method	Accuracy
Saengtabtim *et al.*[10]	Decision tree	88.6 %
Wang *et al.* [15]	DAE model	90 %
Proposed approach	CSO optimized ANN	92 %

5 Conclusion

This research introduces a comprehensive and efficient framework for the detection and classification of tsunami prediction using CSO optimized ANN. The integration of advanced data preprocessing techniques, such as cleaning and visualizing, ensures that the input data are optimized for feature engineering. Additionally, the adoption of speedup data transformation for raw data to certain format data feature extraction enables a detailed and multi-dimensional analysis of the input data, capturing crucial patterns for effective classification. The performance evaluation, conducted on the earthquake dataset, demonstrates the superior capabilities of the CSO optimized ANN compared to existing state-of-the-art methods. By using neural network, the model focuses on critical features, resulting in improved accuracy of 92%.

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