Innovative Earthquake Warning System for Enhancing Public Health Prevention

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KEYWORDS

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ABSTRACT

An earthquake is a sudden ground shaking caused by tectonic activity, posing significant risks to human safety. Effective public health strategies focus on minimizing damage, providing timely warnings, and ensuring response plans to reduce health impacts during seismic events. The purpose of this research is to establish an innovative earthquake warning system for enhancing public health prevention. In this study, we propose a novel Mexican Axolotl Optimization-tuned Adjustable Support Vector Regression (MAO-ASVR) for accurately detecting the earthquake incidents. Our model integrates Internet of Things (IoT) technology to collect data from various sensors deployed across seismically active regions. The obtained signal data is pre-processed using Noise Filtering technique. In our proposed model, MAO optimization algorithm iteratively fine-tunes the ASVR architecture for enhancing the detection accuracy. The system activates an early warning alert within seconds of detecting seismic activity and sends notification, thereby minimizing potential damage. During the findings analysis phase, we evaluate our model's performance across various parameters. In addition, we also performed comparative analyses using diverse existing methodologies such as MAE with 0.397888, PMRE with 19.81432 errors, RMSE with 0.509074 errors. The findings demonstrate excellence and effectiveness of the suggested model.

1. Introduction

Earthquakes are unique of the greatest unpredicted and disturbing social and economic disasters that humanity has ever faced [1]. To limit damage and prevent additional devastation following a quake, it is critical to swiftly deploy disaster aid to affected societies. In general, disaster relief operations concentrate on meeting the needs of people in general [2]. Several conventional as well as contemporary techniques have recently played significant parts in early warning systems (EWS). As a result, effective integration of multiple sciences is desired to support such important systems. Developing an efficient earthquake early warning system (EEWS) involves thorough evaluation of a number of aspects, including the environment and seismic characteristics to be monitored [15]. The home's seismic warning system uses wireless communication methods to warn the robot of any warnings. Earthquakes are natural events that shape the Earth. This happens as a result of a massive amount of energy being released at the border of the plates in the crust caused by floating continental masses known as the plate, which is the earth's top layer [4]. Earthquakes occur in the Lithosphere, which is the earth's uppermost layer located 70-100 kilometers below the surface. This information is then fed into GMPEs (Ground Motion Prediction Equations), which predict ground motion at specified locations. The overall size of early warning systems is calculated manually using multiple records of the wave signal (P) and various features, such as wave amplitude (A) and earthquake duration (T), as well as a function with several uncertainty-related parameters [5]. Seismic fault shifting creates waves P and S; however, the P-wave has significantly smaller average amplitude than the S-wave. An earthquake is a sudden ground shaking induced by tectonic activity that poses a serious threat to human safety [13].

Aim of the study: This study offers a novel earthquake warning system based on the MAO-ASVR model, which incorporates IoT sensors and noise filtering to accurately detect seismic activity [16]. The technology generates early warnings in seconds, reducing potential damage. Performance evaluations and comparative assessments show that the model is excellent at improving public health prevention during earthquakes [9].

2. Related work

Cremen et al. [7] used an upcoming risk-informed earthquake early warning decision-support system (EEW DSS) with multiple-criteria executive to determine the ideal decision [6]. The suggested DSS considered engineering-driven damage estimations for sending or not sending an EEW warning during an incident, as well as possible system failures. The proposed EEW DSS utilized the results of these evaluations, as well as end-user hazard inclinations, to estimate and agree optimum solution for separate situation. Cui et al. [8] were divided into three parts: (I) train with multiple base learners, (II) integrate the results using the stacking technique, and (III) enhance serious restrictions in the prediction model with a better swarm intellect procedure [12]. The stacking group learning approach has been shown to correctly incorporate the base learner's prediction results, increasing model performance, while the enhanced swarm intelligence algorithm may boost prediction accuracy even more. In addition, the relevance of each trait was rated, which has major implications for future earthquake safety and rescue operations. Abdalzaher et al. [14] offered a study of the countless features required for the EEWS. Initially, the IoT system was looked at broadly to provide insight into its potential role in EEWS [3]. Subsequently, ML prototypes were categorized into linear and nonlinear categories. Thirdly, the assessment metrics for ML models were spoken by concentrating on seismic research. Quarterly, the study proposed a classification of developing ML and IoT events for EEWS. Lastly, study covered the submission of ML for seismic parameter measurements, resulting in an efficient EEWS. Chaojun et al. [10] examined cutting-edge EEW procedures from around the world. They focused on the various techniques developed for swiftly determining earthquake foundation restrictions, and thinkable effects in the aftermath of an incident. They likewise evaluated the restrictions of the proposed procedures, with precise importance on the lack of engineering-related pointers that are presently utilized to provision executive concerning the initial of alerts by different end-user. Lastly, they presented several ideas for future end-user-oriented advancements in the pitch of EEW.

3. Methodology

The methodology employs the Mexican Axolotl Optimization-tuned Adjustable Support Vector Regression (MAO-ASVR) to identify earthquakes using a dataset of 59,276 IoT measurements. MAO-ASVR enhances ASVR by optimizing variables utilizing the Mexican Axolotl Algorithm (MAA) to accurately detect earthquake incidents by using the data such as accelerometer and gyroscope to improve detection accuracy and system performance.

Data collection

Dataset are gathered from open source (https://www.kaggle.com/datasets/aaryapandya/earthquake-detection). The IoT dataset has 59,276 total readings. As a result, column 1 indicates an earthquake has happened, whereas column 0 indicates no earthquake. In contrast to the gyroscope, the accelerometer exhibits frequent and significant changes in coordinates. This occurs when the accelerometer indicates a change in acceleration, whereas the gyroscope represents a change in angular velocity.

Detect the earthquake incidents using Mexican Axolotl Optimization-tuned Adjustable Support Vector Regression (MAO-ASVR)

The above explanations show that ASVR associations the structures of SVR. The MAO-ASVR model integrates with an IoT network by collecting real-time seismic data from sensors. This data is processed and analyzed using the MAO algorithm to fine-tune the ASVR model, enabling rapid earthquake detection and issuing early warnings to minimize damage and enhance public safety. In this study, the ASVR using gyroscope accelerometer measured acceleration (aX, aY, aZ) and angular velocity (gX, gY, gZ) is the parameter of the classification to increase prediction accuracy. It fine-tunes the equation using optimization approaches, which account for data variances and improve performance for accurate and adaptable regression analysis in complicated datasets, which iteratively modifies the system's parameters to achieve peak performance. This tuning procedure improves ASVR's ability to reliably detect The ASVR examines the relationship between numerous characteristics to determine which are most closely associated with earthquake detection. The MAO optimization, inspired by the behavior of the Mexican Axolotl, refines this analysis to focus on the most important characteristics, increasing the model's accuracy in identifying earthquakes and allowing the warning system to issue timely alerts that effectively reduce possible harm.

Mexican Axolotl Optimization (MAO): The MAO algorithm inspires axolotl's life. Axolotls inhabit in aquatic environments and require inspiration for reproduction, tissue regeneration, and birth. The axolotl population is separated into males and females. Axolotls are thought to be capable of changing their color, which we believe they do to disguise particular sections of their bodies and evade predators. The MAA algorithm is divided into four iterative phases: injury and restoration, mature state, imitation, and variety, denoted as TIRA. The procedure for highest drive removal exploits the suggested system's competence while minimizing loss. The procedure is described step by step.

The initial procedure includes varied property sizes, female and male populations, tournament sizes, and termination criteria. The population develops at random. Fitness calculation, the scheme loss is reduced based on the independent function, as denoted in Equation (1).

$$e_d = \min\,(o_k^*) \tag{1}$$

As axolotls transition from larvae to grownups, the impartial function has an opposite conversion chance for men and females. This is owing to the choice of the finest male and female. To calculate the converse chance of diffusion for men and women was indicated by Equation (2).

$$O(n,e)_I = \frac{pa_I(n_I,e_I)}{\sum pa_I(n_I,e_I)} \tag{2}$$

The populations of male and female are observed to take a possibility that the price of male is greater than the price of chance, apprise of male populace is provided in Equations (3 and 4), which expresses the body color of male axolotls.

$$n_{IJ} = n_{IJ} + n_{BEST,J} - n_{IJ} * \alpha \tag{3}$$

$$n_{IJ} = min_J + max_J - max_I * q_J \tag{4}$$

αRepresents the diffusion factor, n_I is the male axolotl, and q_J is the chance power. Equation (5) expresses that the probability of female population is fewer than that of random population. The cost of decorated axolotl is indicated in Equation (6).

$$e_{IJ} = e_{IJ} + e_{BEST,J} - e_{IJ} * \alpha \tag{5}$$

$$e_{IJ} = \frac{min}{J} + \frac{max}{J} - \frac{max}{I} * q_J \tag{6}$$

Axolotls travel into the sea, which can lead to fortunes and injury. Axolotls' injury phase refers to the likelihood they will be harmed and lose a body part. The rebirth method is defined as Equation (7).

$$o_{IJ} = min_J + \left(max_J - max_I\right) * q_J \tag{7}$$

After the male has deposited his sperm, the female extracts the gloca from her semen. The statement has been discovered via two eggs. After the laying of eggs, the method of selection begins, with the finest larvae shifting to a favorable place. Verify the ending condition; if it meets this step, the ideal outcome was achieved; otherwise, proceed to fitness calculation.

Adjustable Support Vector Regression (ASVR): ASVR $\hat{z}_{isvr}$ considers the established SVR $\hat{z}_{isvr}$ as a "low-fidelity model," the factual recreation classic $z(W)$ as a "high-fidelity model," and uses correction functions to improve the "low-fidelity model's" overall performance. The procedure can be expressed as:

$$\hat{z}_{isvr}(W) = \hat{z}_{isvr}(\hat{z}_{svr}(W), b) \approx z(W) \tag{8}$$

Here b represents the vector of correction factors. It minimizes the disparity amongst the answers of the "preliminary model" and the "great-fidelity model."Addition-form corrective function is,

$$D_0(W,\beta) = \beta_0 + \beta_1 w_1 + \cdots + \beta_l w_l = d^S\beta \tag{9}$$

Where= $[\beta_0\beta_1 \ldots \beta_l]^S$. S Represents a path of $l+1$continuous constants, when $d = [1\; w_1 \ldots w_l]^S$ and S is a first-order polynomial basis purpose path with $l+1$associates and multiplication-form corrective purpose.

$$\hat{z}_{isvr}(W) = D_1(W,\lambda)\hat{z}_{svr}(W)$$

$$D_1(W,\lambda) = \lambda_0 + \lambda_1 w_1 + \lambda_l w_l = d^S\lambda \tag{10}$$

Where $= [\lambda_0\lambda_1 \ldots \lambda_l]^S$ and S indicates a vector with $l+1$ constant coefficients hybrid-form corrective purpose.

$$\hat{z}_{isvr}(W) = D_0(W,\beta) + D_1(W,\lambda)\hat{z}_{svr}(W) \tag{11}$$

The hybrid-form alteration purpose is chosen to create ISVR. ISVR estimates the β and λ in Equation (11). Equation (11) and the various linear regression analyses appear to closely relate. Multiple linear regression analysis aims to reduce the difference amongst approximate and genuine results. The least squares approach is utilized to estimate βandλ. Using Equation (12) and the provided training dataset (xi, yi) (i = 1,...,m), the following equation can be produced.

$$\begin{bmatrix} z_1 \\ z_2 \\ \vdots \\ z_n \end{bmatrix} = \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_n \end{bmatrix} + \begin{bmatrix} \hat{z}_{isvr,1} \\ \hat{z}_{isvr,2} \\ \vdots \\ \hat{z}_{isvr,n} \end{bmatrix} = \begin{bmatrix} f_1 \\ f_2 \\ \vdots \\ f_n \end{bmatrix} + \begin{bmatrix} 1 & 1 & \cdots & 1 \\ w_{1,1} & w_{1,2} & \cdots & w_{1,n} \\ w_{2,1} & w_{2,2} & \cdots & w_{2,n} \\ \cdots & \cdots & \ddots & \cdots \\ w_{l,1} & w_{l,2} & \cdots & w_{l,m} \\ \hat{z}_{svr,1} & \hat{z}_{svr,2} & \cdots & \hat{z}_{svr,n} \\ w_{1,1}\hat{z}_{svr,1} & w_{1,2}\hat{z}_{svr,2} & \cdots & w_{1,n}\hat{z}_{svr,n} \\ w_{2,1}\hat{z}_{svr,1} & w_{2,2}\hat{z}_{svr,2} & \ddots & w_{2,n}\hat{z}_{svr,n} \\ \cdots & \cdots & & \cdots \\ w_{l,1}\hat{z}_{svr,1} & w_{l,2}\hat{z}_{svr,2} & \cdots & w_{l,n}\hat{z}_{svr,n} \end{bmatrix}^S \begin{bmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_l \\ \lambda_0 \\ \lambda_1 \\ \vdots \\ \lambda_l \end{bmatrix} \tag{12}$$

Where ej indicate the error of $\hat{z}_{isvr}$ at the i^{th}training point (TP), $\hat{z}_{svr,j}$indicate $\hat{z}_{svr}$ at the i^{th}TP, $\hat{z}_{svr,j}$ indicate$\hat{z}_{svr}$ at the i^{th}TP, and wj, i indicate the i^{th}element of thei^{th}TP. Where ejindicate the error of $\hat{z}_{isvr}$at the i^{th}TP,$\hat{z}_{svr,j}$indicate$\hat{z}_{isvr}$ at the i^{th}TP, $\hat{z}_{svr,j}$ indicate$\hat{z}_{svr}$ at the i^{th}TP, and wj, i indicate the i^{th}element of the TP. Equation (11) can be written in medium form as follows. Using the smallest squares method, ζcan be approximated as equation (14).

$$z = \hat{z}_{isvr} = f + V_\varsigma \tag{13}$$

$$\varsigma = \begin{bmatrix} \beta \\ \lambda \end{bmatrix} = (V^S V)^{-1} V^S z \tag{14}$$

Warning system

The early warning alert system for the earthquake detection model takes a multifaceted approach to ensuring timely and efficient communication with the public. When seismic activity is detected using the MAO-ASVR model, the system interfaces with SendGrid to provide users with accurate email notifications, including comprehensive alerts. Firebase Cloud Messaging (FCM) distributes real-time push notifications to Android and iOS devices, ensuring that users receive alerts quickly. Pusher manages web-based notifications, allowing for fast updates to online applications. Node-RED orchestrates the integration of various components, automating the entire process from detection to alert distribution. Grafana is also used to monitor and analyze the system's performance, providing insights into alert delivery and efficiency. This thorough setup ensures a reliable and responsive alarm system, which improves public safety by providing timely warnings during earthquake events.

4. Result And Discussion

The system setup includes a Windows 10 operating system and Python 3.6.4 to put our plan of action into motion. The system has a Radeon RX 7900 XTX graphics card and a Ryzen 7 5800X CPU capable of running heavy machine learning algorithms. In this study we examined the proposed model with the existing approaches such as flower pollination Algorithm- extreme learning machine (FPA-ELM), hybrid of FPA and the least square support vector machine (FPA-LS-SVM) [11] using metrics like MAE with 0.397, PMRE with 19.81, and RMSE with 0.50. These results indicate the system's high accuracy and effectiveness in early earthquake detection and notification.

PMRE: PMRE is an error statistic used to determine the success of earthquake warning systems. It calculates the average differences between the systems believed and actual earthquake detections to assess the MAO-ASVR model's accuracy and reliability, as shown in figure 1. When compared to the existing methods, our proposed model MAO-ASVR achieves less error rate with 19.81.

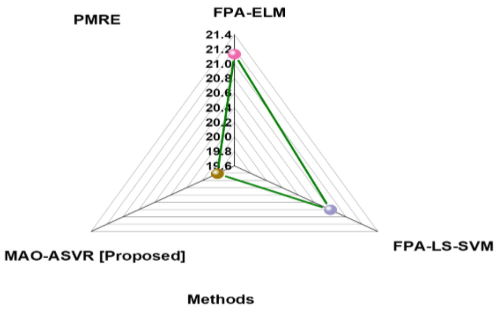

Figure 1. PMRE classification

RMSE: The RMSE is a metric used to assess the correctness of seismic warning systems. It measures the difference between expected and real seismic data, with lower RMSE indicating improved model performance and more accurate earthquake detection in the proposed MAO-ASVR system. When compared to the existing methods, our proposed model MAO-ASVR obtains less error rate with 0.50 (as shown in figure 2(a)).

MAE: The MAE in this context examines the accuracy of the MAO-ASVR model by determining the average magnitude of predicted errors between the model's alerts and actual earthquake occurrences. A lower MAE suggests improved performance in detecting seismic occurrences and issuing timely warnings, as shown in figure 2(b). When compared to the existing models, our proposed model (MAO-ASVR) obtains less error with 0.39. Our proposed model is achieving the loss errors in PMRE with 19.81, RMSE with 0.50 and MAE with 0.397. Table 1 depicts the overall outcomes of existing and proposed methods.

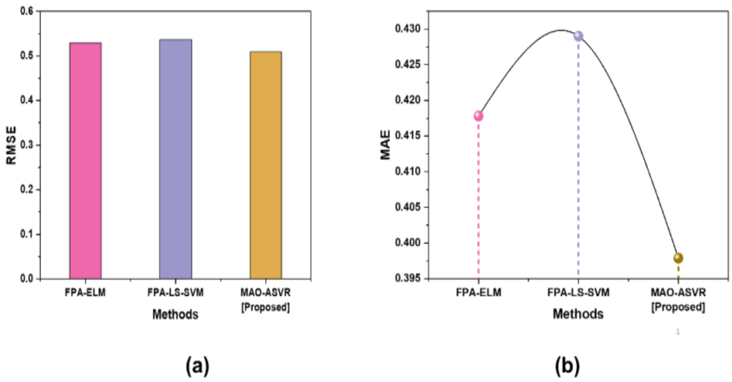

Figure 2. RMSE and MAE Outcomes

Table 1. Classification for PMRE, RMSE, and MAE

Methods	PMRE	RMSE	MAE
FPA-ELM	21.13068	0.529094	0.417803
FPA-LS-SVM	20.80531	0.537101	0.428999
MAO-ASVR [Proposed]	**19.81432**	**0.509074**	**0.397888**

5. Conclusion

This study introduces a novel strategy to earthquake detection and public health prevention by creating the Mexican Axolotl Optimization-tuned Adjustable Support Vector Regression (MAO-ASVR) model.

The system collects and processes seismic data from sensors in active locations using IoT technology and advanced noise filtering techniques. The MAO optimizes the ASVR model, resulting in much higher detection accuracy. This system's early warning notifications can be sent in seconds, allowing critical time for preventative actions while limiting potential damage and health implications. Comparative evaluations reveal that the MAO-ASVR model outperforms other approaches, confirming its efficacy and dependability. This revolutionary approach not only improves earthquake detection but also supports public health efforts by delivering timely and accurate alerts, contributing to enhanced safety. Future research could focus on enhancing the MAO-ASVR model's quality, integrating more data sources, improving real-time alarm systems, and increasing deployment to various seismic locations around the world.

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