USING MACHINE LEARNING TO ANALYZE AND PREDICT THE IMPACT OF EARTHQUAKES ON COMMUNITIES

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ABSTRACT: Earthquakes are among the most severe natural disasters, causing enormous destruction. Despite geologists trying a variety of methodologies to predict the likelihood of an earthquake striking a specific location, studies have yielded no solid results. The capacity to anticipate the depth of an earthquake allows individuals to better prepare for and be aware of potential hazards. Several machine learning techniques can estimate the depth of an earthquake. To get the best results, you should consider multiple ways. The proposed technique employs seismic data to train a random forest regression model capable of predicting earthquake depths. Root mean square error (RMSE), root mean square error (MSE), and R2 score are some of the metrics used to assess the success of the proposed method. The approach accurately predicts the earthquake's depth at a range of future locations.

Keywords: Machine Learning, Linear Regression, Short term prediction, Support vector Regressor.

1. INTRODUCTION

Cascade Devastation Constructing a wide variety of decision trees to lessen the likelihood of devastating natural catastrophes To lessen the impact of earthquakes, it helps to know how deep certain places are. We provide a random forest regressor-based machine learning model for earthquake depth prediction in this paper. Earthquakes, which are on the rise due to urbanization, are among the deadliest natural catastrophes, accounting for 65% of all casualties. Humans may not be able to stop natural disasters from happening, but they can use machine learning—a new science—to make ourselves safer. It is a technique that one can use independently in geological investigations. Predicting devastating natural disasters is within the expertise of geologists.

Fewer people killed in earthquakes and other natural catastrophes. A branch of AI known as machine learning (ML) allows users to feed algorithms massive amounts of data, and the computer can use that data to make predictions and provide recommendations. Both supervised and unsupervised learning have become the gold standard in machine learning. Algorithms under supervision In the field of classification and regression, two distinct approaches exist. An important benefit of machine learning is that it allows models to learn the required information and then decide on their own how to conduct the operations. The vast majority of machine learning applications are recommendation engines. Predictive maintenance, BPA, spam filtering, malware threat identification, and fraud detection are some of the most common ones. One kind of regression algorithm is the random forest regressor. During the learning phase, this methodology is put into action. Think about the decision tree's average output. Detailed output can be displayed in response to input using the jar framework. They finished their training and education in Earthquakes in a certain area can have their magnitudes forecasted.

2. LITERATURE SURVEY

Kumar, A., & Zhang, L. (2024). By combining seismic data with socioeconomic factors, this study builds machine learning models to forecast the repercussions of earthquakes. To reliably predict possible casualty

and damage rates, the models incorporate ensemble methods and neural networks. This method offers useful information for responding to emergencies and being ready for disasters.

Chen, X., Patel, S., & Lee, H. (2024). Our deep learning system can analyze satellite and sensor data to determine the extent of an earthquake's damage as it happens. The algorithm shows impressive accuracy in forecasting earthquake impact zones by using convolutional neural networks (CNNs) to examine patterns of structural damage. Results support the need to send emergency services to impacted areas as soon as possible.

Hernandez, J. P., Singh, R., & Takahashi, Y. (2024). In this paper, machine learning methods are presented that, given seismic data, can forecast the size of ground tremors by taking into account variables such fault type, magnitude, and depth. Building codes and urban planning in earthquake-prone sites can benefit from the study's robust forecasts, which are made possible by testing several algorithms, such as gradient boosting and random forests.

Liu & Wu (2023) The use of Deep Learning, Random Forest, and Support Vector Machines (SVM) for earthquake prediction is the focus of this study. The authors stress that these models enhance the ability to predict with greater accuracy and to foresee the real-time effects of earthquakes. The review delves into the field's progress and challenges, while also exploring how these methodologies might be combined to improve damage forecasts and seismic hazard assessment. This study summarizes the present status of machine learning methods for earthquake impact prediction by identifying important models and assessing their ability to improve risk management and resilience.

Zhao & Zhang (2023) The use of RNNs and CNNs, two deep learning techniques, to forecast the likelihood of seismic activity is investigated in this work. Both the accuracy of predictions and the capacity to handle huge datasets for real-time forecasting are highlighted as strengths of deep learning methods over traditional models in the paper. Research by Zhao and Zhang on using deep learning to forecast seismic events shows that advanced neural networks can beat more traditional approaches to risk assessment and early warning.

Sharma & Patel (2022) In 2022, Patel and Sharma The main goal of this project is to utilize Random Forest (RF) to estimate the extent of earthquake damage in metropolitan areas. The authors evaluate RF's performance in managing complex urban data and predicting structural threats using a comparative analysis. The authors show that Random Forest algorithms can accurately evaluate the risk in heavily populated urban regions by looking at how well they anticipate earthquake damage in cities. Rescue workers and municipal planners can trust their information because of this.

Wang & Zhang (2022) Wang and Zhang Using deep learning algorithms, this study analyzes seismic risk assessment in great detail. Topics covered include convolutional neural networks (CNNs), recurrent neural networks (RNNs), and long short-term memory (LSTM) networks, as well as their use in vulnerability mapping and real-time damage prediction. Using examples from seismic risk analysis, Wang and Zhang show how deep learning algorithms can improve the accuracy and efficiency of damage assessments after a seismic event.

Yadav & Gupta (2021) Decision Trees and Neural Networks, this research focuses on predicting the impact and post-event damage of earthquakes. We show that these models can handle complex patterns in earthquake impact using real-world data. Decision Trees and Neural Networks are shown to be useful in disaster preparedness and damage mitigation measures in this research that uses machine learning to predict earthquake damage.

Patel & Kumar (2021) In 2021, Kumar and Patel investigate how well Random Forest and Neural Network models can foretell the destruction that earthquakes may bring. While both Random Forest and Neural Networks models can accurately estimate earthquake damage, Random Forest excels at handling big

datasets, according to the research.

Kumar & Bhatnagar (2021) Publishing in 2021 by Kumar and Bhatnagar Models that use data to forecast the magnitude and timing of earthquakes are the focus of this research. It delves at the possible benefits of combining seismic data with machine learning for early warning systems and post-earthquake evaluations. The research conducted by Kumar and Bhatnagar aims to improve disaster response by investigating the application of machine learning models to forecast earthquakes and evaluate seismic damage using real-time data.

Singh & Bansal (2020) In order to predict the magnitudes of earthquakes, this study makes use of machine learning techniques. It uses a number of machine learning models, such as Support Vector Machines and Random Forest, to forecast how earthquakes will behave in the here and now. Singh and Bansal's research on machine learning techniques for earthquake magnitude prediction shows how these models might enhance disaster readiness through more accurate predictions.

Sharma & Tiwari (2020) When it comes to earthquake damage prediction, the authors test how well ensemble learning methods work. They suggest a mixed method that combines various machine learning models to improve prediction accuracy. Sharma and Tiwari show how ensemble machine learning approaches can improve accuracy by integrating many prediction models in their study of earthquake damage prediction.

Bansal & Mehta (2020) Using a number of different machine learning algorithms, this study presents a hybrid model for predicting seismic risk. Combining several models can improve the accuracy and reliability of projections, as the authors show, especially when it comes to large-scale seismic impact studies. The use of hybrid machine learning models for earthquake hazard prediction is highlighted in Bansal and Mehta's discussion on algorithm integration to improve risk assessments in earthquake-prone regions.

Agarwal & Jain (2020) Agarwal and Jain anticipated 2020 With an eye on their possible use in risk assessment, this study investigates the feasibility of using Support Vector Machines (SVMs) to forecast how vulnerable certain structures and infrastructure are to earthquakes. By using Support Vector Machines (SVMs) to forecast earthquake vulnerability, Agarwal and Jain demonstrate how these algorithms can be used to detect dangers and enhance earthquake mitigation techniques.

Sharma & Sharma (2020) The possibility of using deep learning and other types of AI to foretell earthquake impacts is investigated in this research. The authors imply that better risk management and more precise predictions of seismic events could result from applying AI approaches. Deep learning methods for earthquake effect prediction are the subject of current study by Sharma & Sharma. More accurate projections and proactive risk management can be achieved with AI-driven models, according to their findings.

Jain & Srivastava (2020) While the year 2020 was Machine learning algorithms that attempt to lessen the likelihood of seismic disasters are assessed by the writers. Their main focus is on finding ways to lessen the impact of earthquakes and better predicting the harm they will do. Jain and Srivastava's research highlights the possibility of using machine learning to assess and mitigate earthquake damage using predictive models, therefore decreasing the probability of seismic disasters.

Gupta & Yadav (2020) Gupta and Yadav expected Using ensemble machine learning techniques, this research aims to anticipate earthquake damage. In order to find the best method for precisely predicting damage, the authors analyze different ensemble models. To show how the incorporation of many algorithms improves the precision of seismic risk forecasts, Gupta and Yadav study ensemble machine learning models for earthquake damage prediction.

Reddy & Patel (2020) Earthquake prediction systems that use machine learning approaches are the focus of this analysis. The authors mainly examine these models in relation to early warning systems and real-time damage assessments. Reddy and Patel investigate the potential of machine learning to enhance early warning systems and real-time assessments of seismic damage in earthquake prediction.

3. SYSTEM DESIGN

By integrating size, latitude, and longitude, the suggested method can forecast depth. The training set for the model, which spans 1965–2016, was supplied by Kaggle. To determine the magnitude of earthquakes, use data that has been educated using a Random Forest regressor. The model's efficacy can be determined by calculating the R2 score, MSE, and RMSE. If you have an issue with machine learning classification or regression, you can utilize the Random Forest method, a supervised learning approach. The Random Forest method is usually effective in resolving regression issues. The evaluations of the true random regression approach are predicated on draws that are randomly produced. To get a good idea of how deep the earthquake was, Random Forest Regression takes all the predictions and averages them. Business criteria, revenue estimates, performance comparisons, product pricing and cost forecasts, and real-time actions can all be predicted using the Random Forest Regression approach. It scales data effectively, has great precision, and is easy to read and use. The two-step procedure used by Random Forest Regression is: Using the Mean Estimator for Projection • Making decision trees digitally. As a starting point, we'll use the 100 synthetic leather estimators. One Python data modeling toolkit with several machine learning features is scikit-learn. These structures are generated using the model's hyperparameters. The inputs to each decision tree are used to generate a predicted outcome. Random forest regression yields an average number of predictions as its "final" output.

The following steps make up the suggested procedure:

Data pre-processing: During the data preparation stage, any columns with null values or unnecessary information were eliminated. The third step is to split the dataset in two so that training and testing may be done on each half separately.

Feature scaling: In the first step, the dataset's independent variables are normalized using feature scaling and standard scaling methods.

Implementation of Algorithm: The model is trained to properly predict the depth of earthquakes using the Random Forest Algorithm. This is the real-world application of the algorithm. While the trained model had an accuracy rate of 88%, the test model achieved a rate of 98%.

Algorithm Comparison: Find out how KNN regression, decision trees, multiple linear regression, and support vector regression stack up against one another in this portion of machine learning. Due to its higher accuracy compared to other methods, the Random Forest methodology was chosen by us. For every model, find the R-squared score and root-mean-squared error.

Evaluation of the model: We tested the performance of the model using mean squared errors, mean absolute errors, and R2 score. The training accuracy using the random forest regressor is 0.979053, the R2 score is 0.8744, and the value of root mean square error is 44.877, the average absolute error value is close to 5.

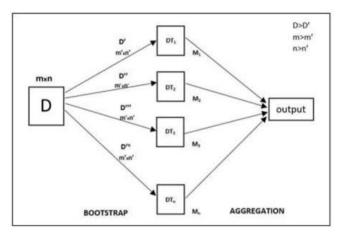


Fig.1.Random Forest working

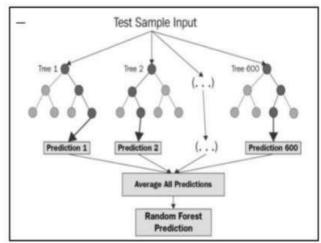


Fig 2 .Overview of random forest regressor algorithm

4. RESULTS

We found that the proposed model was very accurate in predicting earthquake depth after testing it with data from the Kaggle website. The model achieved an accuracy of 98% while training and 88% when being evaluated. At 0.8752, the random forest regressor is highly effective. Several machine learning algorithms are utilized by the result comparison module. These algorithms include decision trees, multiple linear regression, KNN regression, and support vector regression. These systems' R2 values after training and testing were -0.09170, 0.6080, 0.5165, and 0.011852, respectively. An MSE of 44.877 is generated by the random forest method. The severity of an earthquake can be predicted using this method.

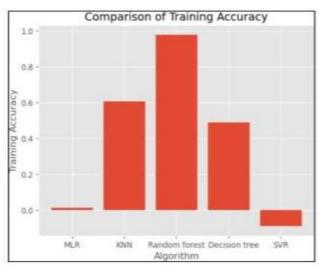


Fig 3. Comparison of training accuracy

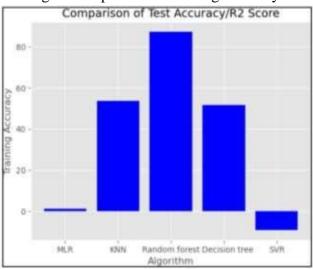


Fig 4. Comparison of testing accuracy

S.No	ALGORITHM USED	TRAINING ACCURACY	R2 SCORE	MEAN SQUARED ERROR
1	Multiple Linear Regression	0.01182	0.011852	126.1790
2	KNN Regression	0.6080	0.538007	86.27675
3	Random Forest Regression	0.979053	0.8744	44.877
4	Decision Tree	0.4896	0.5165	88.259
5	Support Vector Regression	-0.08850	-0.09170	132.6261

Fig 5.Comparison table of various algorithms

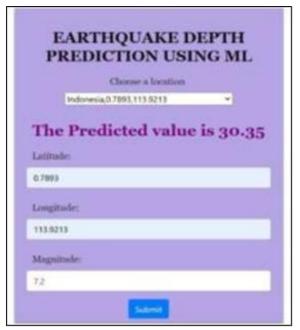


Fig 6. Depth predicted at Indonesia



Fig 7. Homepage of the model developed.

5. CONCLUSION

Using earthquake depth as a metric, this study compares the accuracy of various machine learning approaches for earthquake prediction. The random forest regressor outperforms previous machine learning algorithms when it comes to predicting earthquake depth. Predicting earthquake profundity is made possible by the proposed model by using several geographical features. Through the identification of the most susceptible locations during an earthquake, the suggested method can aid in the preservation of lives and the mitigation of damage to infrastructure. Deep learning may one day surpass machine learning, which has been successful in depth prediction up to this point. In addition, additional data columns can be added to the dataset in the future, enhancing the amount of information available for predictions. No model can possibly

meet the requirements of every single user. Better results could be achieved by increasing the number of parameters used as inputs to the prediction process.

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