Earthquake Damage Intensity Prediction

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Abstract:- The intensity of Seismic damage prediction is an important task that aims to predict seismic events in real time from historical data or seismic time series. Due to the increase in seismic data available over the past few decades, research in the field of seismic event detection has achieved considerable success using neural networks and other machine learning techniques. An earthquake is the negative impact. That it significantly harms a community. An earthquake causes loss of life. The system predicts the intensity of damage to be occurring in an earth quake with the help of previous text data. The system predicts magnitude and depth value. Using this value (Magnitude and depth) predict the intensity of damage. This work, proposes a random forest, K-Nearest Neighbor (KNN), and support vector machine (SVM) for earthquake damage prediction. Finding out the best model from various Machine Learning algorithms to build prediction models, evaluate the accuracy and performance of these models. Among these three methods Random forest regressor algorithm shows the most accurate result with 98% accuracy.

Keywords: *KNN, SVM, Random Forest Regressor, Magnitude, and Depth.*

I. INTRODUCTION

A seismic wave that travels through the earth's rocks causes an earthquake, which is a sudden shaking of the planet. When a kind of energy held inside the Earth's crust is abruptly released, typically when rock masses that are holding each other together suddenly collapse and "displace," seismic waves are produced. The most frequent locations for earthquakes are along geological faults or in small spaces where rock masses shift in relation to one another. Significant fault lines are present everywhere across the enormous tectonic plates that make up the crust of the Earth.

Today's planet is more resilient than in the past, and natural calamities result in fewer fatalities. However, earthquakes still have a high mortality rate. The most fatal calamities historically have been floods, droughts, and diseases, but today's massive annual death toll is typically caused by strong earthquakes and the subsequent tsunamis. Since 2000, the highest yearly death rates were in 2004 and 2010. (Hundreds of Thousands per year).

Earthquake deaths were 93% and 69%, respectively. In fact, the deadliest earthquake in the history of both events (the Sumatran earthquake and the tsunami) occurred in 1556 in Shaanxi, China. It is estimated that 830,000 people were killed. The 316,000 deaths reported in Haiti in 2010 were due to the 2004 earthquake and the 2010 Porto Prince earthquake, which ranks the deadliest earthquakes below.

➢ *Main Causes of Earthquake*

- Plate tectonics: They are responsible for the vast majority of earthquakes that occur worldwide and often take place at tectonic plate boundaries.
- Induced quakes: It is brought on by human activity like tunnel construction, reservoir filling, and geothermal energy or hydro fracturing projects.
- Volcanic quakes: They have a connection to current volcanic activity.
- Collapse quakes: Subsidence can be brought on by events like landslides, which typically occur in karst regions or close to mining operations.

➢ *When an Earthquake Occurs, Different Types of Energy Waves are Generated.*

- The first waves to be recognized are P waves, often known as primary waves. These waves are compressive, pushing and pulling through liquids and rock.
- S waves, sometimes known as secondary waves. The waves can only travel through rock. They oscillate in the same plane as the wave, either up and down or side to side.
- P and S waves are surface waves. They move throughout the surface of the earth and hence do the most harm.

II. RELATED WORK

➢ *Ujwala Bhangale , Surya Durbha , Abhishek Potnis, Rajat Shinde [1] , Rapid earthquake damage detection using deep learning from VHR remote sensing images,2019*

For the detection and evaluation of earthquake damage, Very High Resolution (VHR) remote sensing optical imagery offers a vast source of data. Time-sensitive tasks like damage assessment and the prompt delivery of aid necessitate a rapid response; however, processing large amounts of VHR imagery using computationally expensive but highly accurate deep learning techniques necessitates HPC capability. Deep convolution neural network (CNN) model is specifically built for earthquake damage detection utilizing remote sensing data and implemented using high speed GPU without compromising the execution time in order to maximize the accuracy. For analysis, Geoeye1 VHR disaster photos from the 2010 Haiti earthquake are used. On the GPU.

K80 High Performance Computing (HPC) platform, the proposed model shows significant execution speed and offers good accuracy for damage identification.

Deep CNN is well known for accurately visual object recognition. It has also been shown to be helpful for geographical item detection in the field of remote sensing. Considering its characterization capabilities, a deep learning model is created for disaster data for binary classification utilizing remotely sensed VHR satellite photos to extract visual elements such as debris, shattered roof, etc. for earth-quake damage identification.

- *Masoud Moradi and Reza Shah-Hosseini [2], Earthquake Damage Assessment Based on Deep Learning Method Using VHR Images,2021*

Checking the status of damaged buildings is one of the many important responsibilities involved in conducting rescue efforts following an earthquake. There are two sorts of ways to get the damage map. In order to provide a customizable damage map based on the information that is accessible to us, the first set of approaches uses data both before and after the earthquake, and the second group only uses data after the earthquakes that we want. In this study, we use UNet, a convolution network, and VHR satellite photos of Haiti. To enhance the outcomes, the learning system underwent significant alterations with the goal of identifying the earthquake-related building damage. One of the issues we wish to address is the need for training data that the deep learning algorithms demand. In addition to earlier tests looking at pixel-by-pixel degradation, ultimate precision has increased, demonstrating the success of this strategy and enabling it to achieve an overall accuracy of 68.71 percent. The suggested approach should be employed for other natural calamities including meteors, explosions, tsunamis, and floods that also cause the destruction of buildings in metropolitan areas.

- *Kasim A. Korkmaz1 , Munther Abualkibash [3] , Earth- quake Damage Detection Using Before and After Earthquake Satellite Images,2018*

Since there have been several earthquakes throughout the world, both scholars and practitioners have given earthquake damage assessment a lot of attention. Complexity and unpredictability in many real-world issues call for fresh approaches and solutions. One of these tools that can be employed effectively for increased benefits is image processing. After an earthquake, image processing is used to accurately and quickly determine earthquake damage. After an earthquake happens, damage inspection is made easy by using before and after event photos. In this study, computer vision and image processing techniques were used to identify earthquake damage. A city model was used to create a representative damage detecting procedure. Additionally, satellite images collected before and after the March 11, 2011, Miyagi earthquake in Japan were used toidentify earthquake damage. When assessing the visual damage to structures, pre- and post-event images were compared and urban areas were taken into account. Damage assessment using image differences generates a damage profile in the structural regions of residential buildings, highway bridges, and infrastructures. Using this evaluation, the rescue crews can swiftly identify the damaged urban surfaces after an earthquake.

- *James Martin Lucien Audretsch [4],Earthquake Detection using Deep Learning Based Approaches,2020*

Finding seismic events in historical data or in real time from seismic time series is one of the most crucial jobs in earthquake detection. The availability of more seismic data in recent years has tremendously benefited studies on the identification of seismic events using neural networks and other machine learning techniques. Big data innovation is being stifled by the challenging process of producing high-quality labeled data sets, which necessitates a lot of effort and skill. How many noise and earthquakes are inadvertently included in a data collection is uncertain. Encouraging the widespread application of the machine learning-based models to several geographical regions is another difficulty. The detection in other sites should be compatible with the models thatwere trained using data sets from one place. In order to develop a single location identification model, this thesis investigates convolutional neural networks (CNN), the most well-known deep learning model. Additionally, we employ transfer learning and meta learning to construct more reliable generalized earthquake detection models. We also present a method for creating highly accurate labeled datasets.

Even with low signal-to-noise ratio occurrences, our method delivers good detection accuracy. The AI methods investigated in this study may be applied to other fields where signal processing is used.

There are many potential uses, with audio processing likely being one of the more significant ones today. The proposed methodologies can be used to any field that deals with waveforms (such as seismic, audio, or light).

III. METHODOLOGY

Earthquake damage prediction in this context is based on a multivariate analysis. It has two possible output labels: magnitude and depth. If magnitude value is greater than 7 there is a chance of occur earth quake damage and if the depth value is greater than 40 major earthquake damage is predicted.

magnitude level	category	effects
less than 1.0 to 2.9	micro	generally not felt by people, though recorded on local instruments
3.0–3.9	minor	felt by many people; no damage
4.0–4.9	light	felt by all; minor breakage of objects
5.0–5.9	moderate	some damage to weak structures
6.0-6.9	strong	Moderate damage in populated area
7.0-7.9	major	Serious damage over large areas, loss of life

Fig 1 Magnitude Values

- *System Architecture*

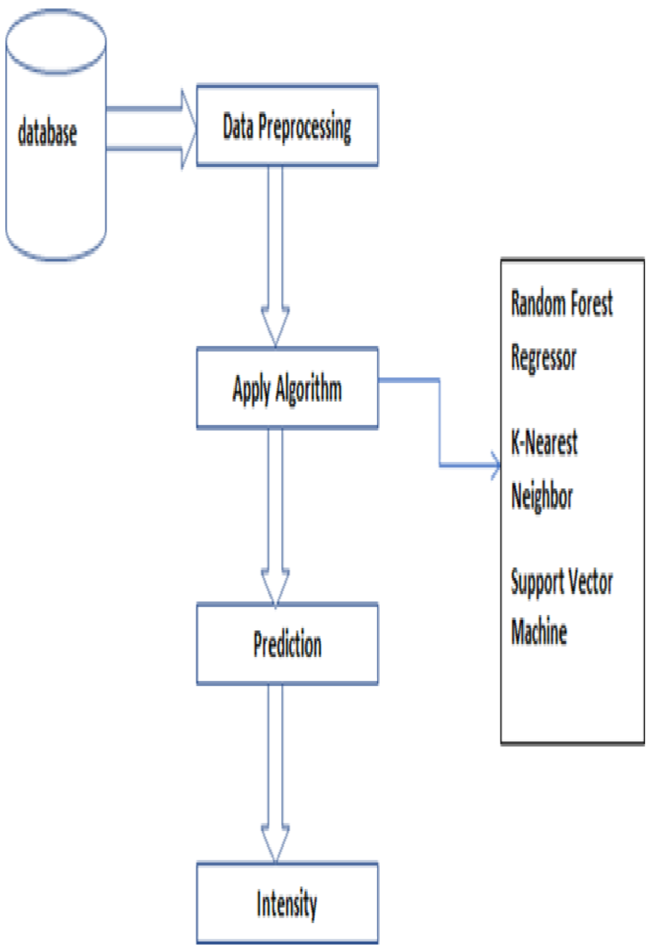


Fig 2 System Architecture

- *Random Forest Regressor*

Random Forest is an ensemble methodology capable of handling both regression and classification tasks. Every decision tree has a significant variance, but when we mix themall in parallel, the variance is reduced since each decision tree is perfectly trained using that specific sample of data, so the output is dependent on numerous decision trees ratherthan just one. The majority voting classifier is used to determine the final output in a classification challenge. The final output in a regression problem is the mean of every output. We use a random forest regressor to predict that magnitude is 5.789200000000017 and the depth is 42.024000000000015.Here we calculate depth values greater than 40 major seismic damage is occurred.

```
/usr/local/lib/python3.7/dist-packages/ipykernel_l
  after removing the cwd from sys.path.
Accuracy of Randomforest 0.9806691882063775
```

- *Support Vector Machine*

Both classification and regression are performed using supervised machine learning techniques known as Support Vector Machines (SVM). The most relevant phrase is categorization. The SVM method aims to find a hyperplane in an N-dimensional space that clearly classifies the data points. With SVM the magnitude is predicted to be 5.7813999999999774 and the depth is 43.03100000000004.Here a depth of more than 40 indicates major seismic damage is occur.

```
/usr/local/lib/python3.7/dist-packages/sklearn/model_
  self.best_estimator_.fit(X, y, **fit_params)
Accuracy of SVM 0.978902303352446
```

- *K-Nearest Neighbor*

One of the most fundamental supervised learning-based machine learning algorithms is K-Nearest Neighbor. The KNN algorithm groups new instances in the category that is most similar to the ones that already exist, assuming that new cases and data are related to examples that already exist. The KNN (*K-Nearest Neighbor*) algorithm keeps track of all the data that is already available and sorts new data into groups based on similarity. So, using the KNN (*K-Nearest Neighbor*) approach, fresh data may be quickly categorized into sets of wells as it becomes available. Using KNN to predict the magnitude is 5.8 and depth is 33.0.Here we calculate depth value greater than 40 major seismic activity (high damage is occur) and less than 40 minor seismic activity.

```
Accuracy of KNN 72.04345727785977
```

IV. DATASET

The dataset is collected from Kaggle. In Kaggle lanldataset is collected. Using required features, predict the earthquake damage.

Table 1 Collected from Kaggle

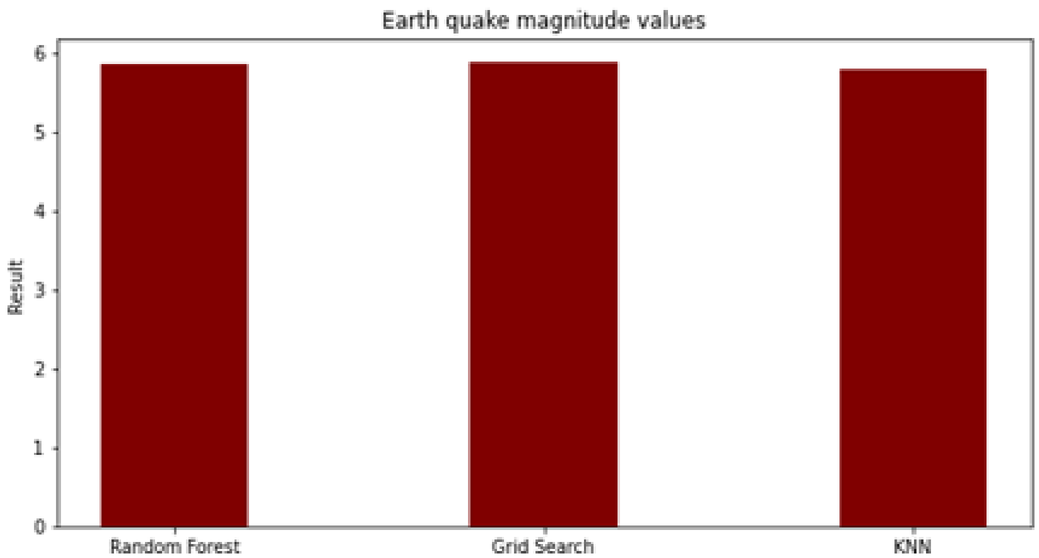
S No.	Date	Time	Latitude	Longitude	Depth	Magnitude
0	01/02/1965	13:44:18	19.246	145.616	131.6	6.0
1	01/04/1965	11:29:49	1.863	127.352	80.0	5.8
2	01/05/1965	18:05:58	-20.579	-173.972	20.0	6.2
3	01/08/1965	18:49:43	-59.076	-23.557	15.0	5.8
4	01/09/1965	13:32:50	11.938	126.427	15.0	5.8

Table 2 Dataset In Kaggle

Columm Name	Description
Magnitude	Earthquake Magnitude Is A Measure Of The "Magnitude" Or Amplitude Of Seismic Waves Produced By Seismic Sources And Recorded By Seismometers. (The Types And Characteristics Of These Waves Are Described In The "Seismic Waves" Section.) Because Earthquakes Vary In Strength, It Is Necessary To Compress The Range Of Wave Amplitudes Measured By A Seismometer Using A Mathematical Tool For Comparison.
Depth	The Strength Of Earthquake Induced Shaking Decreases With Distance From The Epicenter, So The Strength Of Surface Shaking Caused By An Earthquake At A Depth Of 500 Km Is Much Less Than That Of An Earthquake From The Same Earthquake. 20 Km Deep.
Latitude And Longitude	Latitude And Longitude, A Coordinate System Capable Of Determining And Describing The Location Or Location Of Any Place On The Earth's Surface

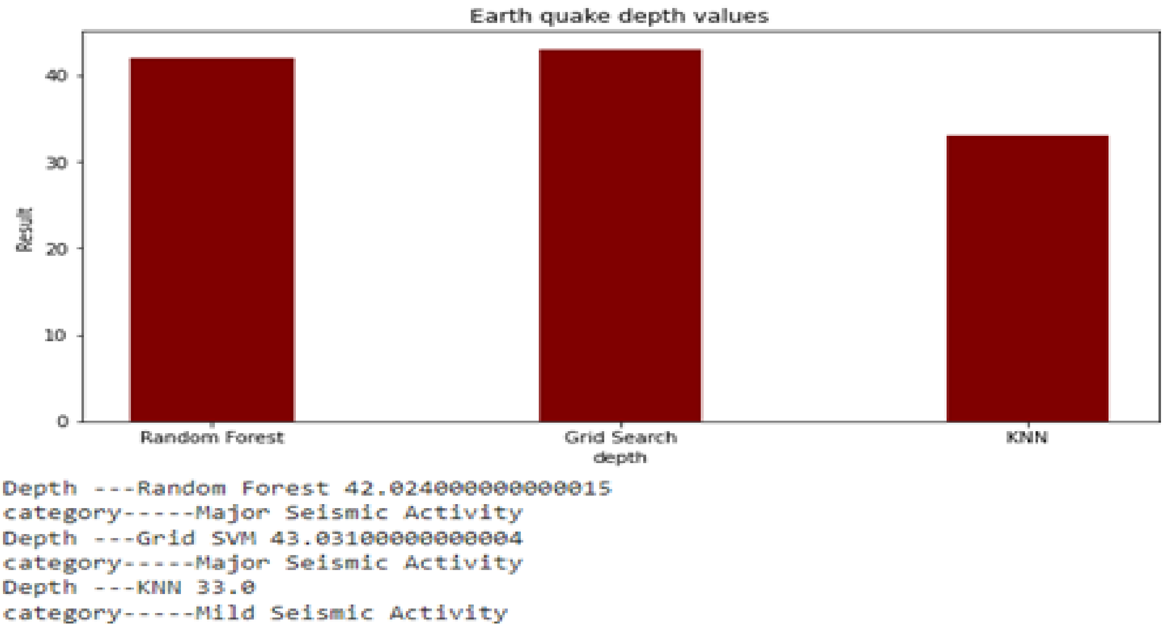
V. RESULTS

- *This Graph Shows Magnitude Values*



Graph 1 Earth Quake Magnitude Values

➢ *The Depth Value Prediction of these Three Algorithms is Different. This Graphs ShowsDepth Value:*



Graph 2 Earth Quake Depth Values

Table 3 Accuracy

Model	Accuracy
Random Forest Regressor	98%
K-Nearest Neighbor	72%
Support Vector Machine	97%

VI. CONCLUSION

This work presents three methods for predicting earthquake damage. Among these three methods, random forest regressor is the most accurate. It gives 98% accuracy. Using magnitude and depth, this work predicts the earthquake damage. This by can be understand unexpected earthquake damage.

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