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Early Earthquake Prediction Using Machine Learning Technique for North Part of India Saving Human Life

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ABSTRACT

An earthquake is a powerful natural disaster that causes the earth's surface to tremble abruptly. Earthquakes harm infrastructure and buildings, which impacts daily life. The originality of this work is that machine learning can be a powerful tool for early seismic impact prediction. With the use of six different machine learning classifiers—Artificial Neural Network, Random Tree, CHAID, Discriminant, XGBoost Tree, and Tree-AS—and six datasets from different regions of India, this understanding was evaluated. Every method has been applied to every dataset.

The study intends to forecast future earthquake magnitudes in India and the surrounding areas using historical earthquake data. With 98.20% accuracy for the Himachal Pradesh dataset, 89.10% for the UttraKhand dataset, 99.13% for the North India dataset, 98.21% for the North East India dataset, 97.50% for the Uttar Pradesh dataset, and 90.00% for the Nearby India's Country dataset, XGBoost Tree was shown to have the highest accuracy. All things considered, the XGBoost tree classifier did well across the majority of datasets.

Keywords: Earthquake, Machine Learning Classifiers, Curve Fitting, Prediction, Neural Network

1. INTRODUCTION

Earthquakes are terrible natural disasters that can destroy large areas of land, destroy property, and kill people. Thus, in addition to hazard, risk, and mitigation planning, earthquake prevention, prediction, and probability monitoring are crucial. China, Taiwan, Japan, the United States, and Chile are among the nations that have expanded their earthquake research and built early warning systems. However, due to their inability to produce satisfactory results, classical methods are rarely employed in the modern hazard assessment or seismic monitoring.

Studies on earthquake prediction include statistical, mathematical, and computational modeling of earthquake parameter data from historical catalogs of seismic zones, genetic mutations and biology, and pure theoretical geophysics. The most important attempts to forecast the three primary earthquake parameters—the epicenter location, the magnitude, and the time of occurrence. In the meantime, roughly 16 earthquakes annually have the potential to cause enormous financial losses and fatalities as well as to trigger secondary calamities like landslides, tsunamis, fires, liquidations, etc. To give a few painful examples, on February 06, 2023, two earthquakes with a magnitude of 7.8 struck Turkey, resulting in an estimated economic loss of about 104 billion. In the meantime, 1.5 million people are now homeless and 50,500 individuals have died. Japan had a terrible tsunami and a major nuclear catastrophe on March 11, 2011, when an earthquake of magnitude 9.0 rocked the country. This disaster caused up to 210 billion dollars in financial losses and at least 22,200 fatalities or reported missing persons.

(Kanamori et al. 1997; Allen & Kanamori 2003; Wu & Kanamori 2005a) It is well known that the Earthquake Early Warning (EEW) approach may effectively lower the seismic risk. The EEW system (EEWS) forecasts the resulting detrimental ground motion to

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notify the public before destructive seismic waves reach the target site. People are therefore given a few to tens of seconds to put emergency mitigation strategies into practice (Allen & Melgar 2019).

Regional and on-site are the two basic forms of EEWSs (Allen et al. 2009b). The target area of the regional EEWS is situated far from the earthquake source area, but the seismic network is situated near the source zone. However, in the case of regional EEWSs, an alarm cannot be set off until harmful seismic waves have reached locations that are too close to the source. The primary component of the on-site EEWS is the single sensor that is placed at the target region. Additionally, by employing P-wave signals at the same location, the on-site method may determine the maximum ground-shaking amplitude of ground motion. Consequently, it is possible to sound an alarm in the source location without requiring a precise assessment of the source parameters.

Climate change is the term used to describe any shift in the climate that can be measured by statistical measures such as the global mean surface temperature. In this context, the term "climate" refers to the long-term pattern of weather that has characterized the last three decades. Climate is affected by a variety of elements, including temperature, humidity, precipitation, air pressure, wind speed, evaporation, cloud cover, condensation, radiation, and evapotranspiration. Earth's climate and temperature are increasingly being influenced by both natural elements, such as variations in solar radiation, and human activities, such as the burning of fossil fuels and deforestation. Changes in the ratios of solar energy and infrared radiation that the Earth emits are the main causes of climate change.

Seismic risk is one of the main concerns for public officials in seismically active locations. Earthquake Early Warning Systems (EEWS) are advanced infrastructures that can lower the seismic risk to people and related losses by rapidly analyzing seismic waves (Gasparini et al., 2011). By analyzing seismic data in real-time, EEWS usually uses the first few seconds of P-wave signals to automatically detect and predict the size of earthquakes. Generally speaking, EEWSs attempt to predict ground motion (such Peak Ground Acceleration, or PGA) at preset targets using these bits of data. As a result, EEWSs notify targets when the shaking strength is expected to surpass a damage threshold.

There are two primary types of EEWS: regional and on-site (Satriano et al., 2011). A single station or a small seismic network is placed close to the target during the on-site approaches. However, in regional systems, a seismic network is positioned close to the seismogenic zone, which is often sufficiently distant from the target area to provide protection. Additionally, on-site systems use empirical scaling laws to predict ground motion directly from P-wave data, whereas regional systems use P-wave and S-wave data from stations around the epicenter to estimate the source's position and magnitude. To predict ground motion at targets, this data is subsequently entered into GMPEs (Ground Motion Prediction Equation).

In the last several years, machine learning (ML)-based techniques and algorithms have demonstrated encouraging outcomes in earthquake prediction. For the purpose of offering a thorough analysis of earlier research, we therefore collected 31 studies on earthquake prediction using machine learning algorithms that were published between 2017 and 2021. This study looked at a variety of global geographical areas. Predicting the magnitude, trend, and incidence of earthquakes is the primary goal of the majority of the models examined in this study. The best seismic indicators were found using a high-performance machine learning algorithm after a comparison of several seismic indicator kinds and algorithm performance.

It has cost enormous sums of money and entire academic careers to predict the location and date of the next great earthquake. In contrast to weather forecasting, which has significantly improved with the arrival of better satellites and more powerful mathematical models, earthquake prediction has frequently failed due to the incredibly changeable properties of the planet and its surroundings. Many specialists now assert that improvements in the analysis of enormous amounts of seismic data, made possible by artificial intelligence, would help them better understand earthquakes, forecast how they will behave, and provide early warnings more rapidly and precisely.

For many builders and real estate companies, this aids in danger evaluations for infrastructure development from a business standpoint. The abrupt release of stress from rocks under stress from a variety of sources, most commonly the gradual movement of tectonic plates, is what causes earthquakes. Although the majority of earthquakes are either insignificant or undetectable to humans, those with magnitudes higher than five have the potential to cause fatalities and damage to infrastructure. Here are a few possible ways machine learning models can be used with this dataset:

1) Earthquake prediction: Using historical earthquake data, you may use this information to create a model that forecasts the potential time and location of an earthquake. Techniques like time series analysis, clustering, or classification can be used to find trends in the data and forecast future events.

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Research Article

2) Magnitude prediction: By using this information, you can create a model that forecasts an earthquake's size based on additional variables like location, depth, or the quantity of seismic stations that recorded the event. Regression techniques could be used to construct this model.

3) Using historical earthquake data, you may use this information to determine which places are more likely to experience earthquakes. To find trends in the data and pinpoint regions with comparable traits, you could apply clustering or classification approaches.

4) Anomaly detection: This information can be used to identify outliers or abnormalities, which may indicate unexpected or uncommon earthquakes. To find trends in the data and spot irregularities, you could apply methods like clustering or classification.

5) Data visualization: This dataset can be used to generate earthquake data visualizations that may aid in the discovery of trends and connections within the data. To illustrate the data, you could employ methods like heat maps, scatter plots, or geographic information systems (GIS).

II.LITERATURE REVIEW

The most frequent earthquakes are caused by plate motions, such as when two plates move parallel to one another (as in the case of the San Andreas fault), away from one another (as in the case of the East African Rift), or toward one another (as in the case of the Himalaya Mountains. [1].

Accurate earthquake forecasts can prevent infrastructure damage and save lives in areas that experience frequent earthquakes. In the past, a variety of prediction techniques have been used, such as radon emissions in wells. [2]

The effectiveness of earthquake prediction with the minimum area of alert method is evaluated after aftershocks are removed from the seismic catalogs. For testing, the Mediterranean and Japanese earthquake catalogs from 1988 to 2019 were employed. The results are compared between employing grid fields calculated from entire catalogs and catalogs with aftershocks removed to predict just big shocks and predicting target earthquakes with aftershock sequences [3].

Various data sources, such as earthquake catalogs, geodetic time series [4], geophysical [5], geochemical [6], and airplane observations [7], are used to describe the seismotectonic features of the geological environment. The ability to simultaneously assess the spatial and spatiotemporal properties of the seismic process, as well as the comprehensiveness of the description of these features, have a substantial impact on the efficacy of seismic hazard forecasting. All available information about the attributes of the process is converted into grid fields in our collaborative analysis approach [8].

In the article, various rule-based, fuzzy, and machine learning-based expert systems for earthquake prediction are discussed. Also discussed are the techniques and regional and worldwide seismic data sets that are used to forecast earthquakes for various geographical areas. According to study kind, empirical kind, approach, target area, and system-specific features, the publications have been categorized for bibliometric and meta-information-based analysis. Finally, a taxonomy of earthquake prediction techniques and the evolution of research over the past ten years are presented [9].

Assessment of seismic hazards requires seismic zoning [10]. The most significant and intricate seismic zoning issue is mapping the highest earthquake magnitudes that can occur (*Mmax*). It is impossible to measure the values of *Mmax* with an instrument. A digital map of *Mmax* is created under two assumptions: (1) that there would be a lot of earthquakes [11] and (2) that the values of *Mmax* will depend on the characteristics of the geological environment [12,13]. This study looked at several parts of the world. Predicting the magnitude, trend, and incidence of earthquakes is the primary goal of the majority of the models examined in this study. To find the best seismic indicators with a high-performance machine learning algorithm, a comparison of several seismic indicator kinds and algorithm performance was compiled. In order to achieve this, we have talked about the ML algorithm's best performance for predicting earthquake magnitude and offered a possible algorithm for further research[14].

The forecast's experts gather historical information on an earthquake's energy, location, depth, and magnitude using earthquake databases. Area-specific earthquake parameters, like b-value parameters, are calculated using the completeness value magnitude as a foundation. Seismic indicators, such as mean magnitude, time lag, earthquake energy, Gutenberg Richter b-values, etc., are typically computed using machine learning (ML)-based methods [15]. On the other hand, models that rely on deep learning (DL) are capable of independently computing thousands of complex features [16], [17]. Since ML and DL-based models rely on data, it is challenging to predict major earthquakes using historical data. However, large earthquakes only happen in a tiny number of cases. To forecast the big earthquakes, several methods employ weights or independent training, but these models require a lot of effort

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https://www.jisem-journal.com/

Research Article

[18].

Gravity was measured close to the epicenter of the earthquake using a mobile gravity survey that produced satisfactory gravity values. Thus, recent understanding of gravity and magnetic changes in earthquake-prone locations can be used to anticipate earthquakes based on precursors [5]. India has seen some of the world's largest earthquakes, and the field of earthquake research has advanced rapidly there [19].

Therefore, India is now establishing seismic codes, structures that are earthquake-resistant and code-compliant, as well as the requisite research facilities, education, training, and institutional development [20].

To predict earthquake magnitude in the southern California region, Adeli et al. used a probabilistic neural network on seismic indicators. The model performed well for magnitudes between 4.5 and 6 [21]. An artificial neural network was used by Moustra et al. in the Greece region to predict earthquake occurrences using time series data and seismic electric signals; two case studies ultimately showed that NN can produce accurate predictions when provided with the appropriate data [22]. Hegazy et al.'s optimized ELM with the flower pollination algorithm (FPA) exhibits enhanced accuracy when used for prediction tasks [23].

Earthquake early warning (EEW) systems are capable of identifying an earthquake's location and magnitude in a matter of seconds and alerting the target area before the destructive waves reach there (24, 25). By warning people to seek shelter, slowing and stopping trains, opening elevator doors, and many other uses, this new technology can lessen the number of earthquake-related deaths, injuries, and damages (26). Traditional seismic and geodetic networks, which are only found in a few nations worldwide, have been the main focus of EEW development up to this point (27).

The positions of seismograph stations that are activated by ground shaking and a series of detected waves (arrival timings) can be used to solve the localization problem. One of several network architectures, the recurrent neural network (RNN), is perfect for controlling a collection of seismic stations that are activated sequentially based on the seismic wave propagation patterns because it can accurately extract information from a series of input data. This approach has been researched to increase the effectiveness of real-time earthquake detection and source characteristic categorization [28].

The accuracy of the aforementioned machine learning-based frameworks may be impacted by a common problem, though, which is that choosing input features frequently calls for specialized knowledge. Identifying the precise locations of an earthquake's hypocenters [31] or regionalizing its epicenters [30].

Early warning for earthquakes, or EEW, is crucial to lowering the risk that natural disasters pose to human life. Many studies have been conducted to develop strategies for reducing the consequences of earthquakes (EQs) by utilizing modern technologies, including the Internet of Things (IoT) and others.[32]. According to Hossin and Sulaiman's review [33], a variety of metrics can be used to evaluate the effectiveness of various machine learning models. Analyzing several factors, such as the location and magnitude of the EQ, is essential for creating an efficient EEWS. Human life can be significantly saved by accurate and timely estimations of factors such as peak ground acceleration (PGA), which determines the intensity on-site [34, 35].

Creating models In order to predict the likelihood of an earthquake in a given area, earthquake forecasting has historically relied on the location of fault characteristics or parameters, such as depth, magnitude, length, latitude, longitude, and time, as well as precursors, such as plant and animal movement, temperature changes, pressure changes, and radon gas. Through the use of data mining techniques for forecasting, the magnitude of earthquakes is concurrently predicted using all available fault parameters and precursors, eliminating the possibility of competing forecasts [39].

In recent years, numerous research have successfully used theoretical, mathematical, computational, and statistical methods to anticipate earthquakes. A review of earthquake prediction utilizing various optimization techniques was recently published by the authors [36]. Few studies have used geological observations and historical data of a specific area or nation to support features that are significantly connected with seismic activity, thus choosing the right data sets is crucial. In order to give a strong logical preprocessing data with independent and dependent features, the literature's works addressed the selection of parameters and antecedents using various data sets. As a result, the preprocessed data is converted into a distinct and reliable data set that can be used with a number of techniques, including regression, KNN, SVM, random forest, decision trees, and random forest [37, 38].

Predicting earthquake magnitude has seen a sharp rise in the use of deep learning, a branch of machine learning. When investigating the temporal and spatial correlations present in seismic data, recurrent neural networks (RNNs) and convolutional neural networks (CNNs) have demonstrated encouraging outcomes. Furthermore, Bao et al. (2021) demonstrated that prediction performance has

Journal of Information Systems Engineering and Management
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Research Article

been greatly enhanced by the coupling of deep learning with ensemble and transfer learning methodologies.

III.MODELLING

The model was constructed using IBM SPSS Modeler. When modeling, each dataset has been split into two halves, called Training and Testing, which make up 70% and 30% of the total. The identical configuration was used to create each model for every dataset. Six distinct classifiers have been used for every dataset in order to train the model. The following is the description of classifier algorithms.

3.1Artificial Neural Network

Another name for artificial neural networks (ANN) is neural networks. Neurons, which are present in the human brain, make up its composition. As nodes, these neurons are connected. Each link transmits the information to other neurons. The neuron sends the information to the other neurons for additional processing after collecting and evaluating it. The output of the neuron is a non-linear function of the sum of its inputs, while the input is a real value. These connections are referred to as edges. The weights of the neurons and edges shift as learning proceeds. These neurons are grouped together to form the layers. The number of layers can be altered based on the input. The inputs are transformed differently by each layer.

3.2Random Tree

One type of random tree is the supervised classifier. There is one significant distinction between how a random tree and a decision tree operate. A random subset of characteristics is used in each split of the Random tree. Many individual learners are produced using the ensemble learning algorithm. The bagging method is used to create the random data sent for a decision tree. Both classification and regression issues can be solved with this approach. The collection of arbitrary trees creates a random forest. Using the random trees approach, each tree in the forest processes the input feature for a classification problem before allocating the class label outputs with the highest number of votes. A random subset of the data and a random subset of the characteristics are used to train each decision tree in the random forest technique. The average (for regression) or the mode (for classification) of the predictions made by each individual tree is the final forecast. Random forests can lessen the effects of overfitting and increase the model's accuracy and stability by generating a large number of trees and averaging them. After dividing the target into parent nodes, CHAID analysis generates child nodes using statistical techniques. CHAID does not require regularly distributed data, in contrast to regression. Merging: The chi-square test is used for categorical dependent variables in CHAID analysis, whereas the F test is used for continuous ones.

3.3CHAID

The decision tree technique is used in the supervised classifier algorithm known as chi-square automated interaction detection (CHAID). CHAD is useful for both prediction and categorization. CHAID's multiway split makes it simple to analyze the results. Nominal, continuous, and ordinal data can all be used in CHAID. For every predictor, it generates every conceivable cross table until the optimal result is obtained. It generates the target variable as the root for the tree's growth. Two categories are created from the target variable, and these become the root's child nodes. Normalized data is not required for the CHAID analysis. A statistical method used in market research is called CHAID analysis (Chi Squared Automatic Interaction Detection). Its primary purpose is to identify the traits most closely linked to a particular result or group membership.

3.4Discriminant

A supervised classification algorithm called the discriminant is employed to lower the dimension. Two or more classes are modeled using it. It takes into account the fact that various classes generate data using various Gaussian distributions. Gaussian distribution parameter estimation is done using the fitting function. The discriminant is a more sophisticated kind of logistic regression. Logistic regression is used for classifying binary classes; however, logistic regression does not support multiple class classification; hence, discriminant can be used in place of logistic regression.

3.5XGBoost Tree

Journal of Information Systems Engineering and Management
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Research Article

Supervised machine learning classifiers are another name for Extreme Gradient Boosting (XGBoost) Trees. The Greed Function Approximation is where the phrase "Gradient Boosting" originates. It is an ensemble approach that is based on decision trees. XGBoost uses the gradient descent architecture for week learners.

3.6.Tress-AS

The supervised machine learning classifier method Tree-AS is also utilized for output prediction modeling. It operates similarly to a decision tree and is a tree classifier. The ability to apply the decision rule at a different level of categorization and employ different feature subsets is the decision tree's advantage. The internal node, leaf node, and root node make up the tree. The dataset's attributes are represented by internal nodes, while the outcome is represented by branches and the class by leaf nodes. Usually, the tree begins at the root node and splits the source into a subset according to the characteristics' features. Splitting is done up till the leaf node in this recurrent procedure.

3.7 P-Wave Features

A Butterworth narrow bandpass filter is used to filter waveforms between 0.5 and 2 Hz. The decision was taken in response to Astorga et al. (2019) and is driven by the desire to choose signals that have a strong correlation with the structural response. In fact, the co-seismic fundamental frequency for the buildings investigated in this study typically falls within this range (Astorga et al., 2020).

IV.Result and Performance

Regarding the test dataset, the accuracy of every model result has been documented. Each classifier's variance, standard deviation, recall, accuracy, precision, F-measure, and standard mean error have all been computed.

4.1Result of Himachal Pradesh Earthquake Prediction

The following is the prediction result for the Himachal Pradesh dataset, where XGBoost Tree has the greatest accuracy of 97.70%. XG-Boost has a precision rating of 97.10 and a recall of 97.70%. Figure 1 showed how various machine learning algorithms with varying performance parameters performed and classified the data set.

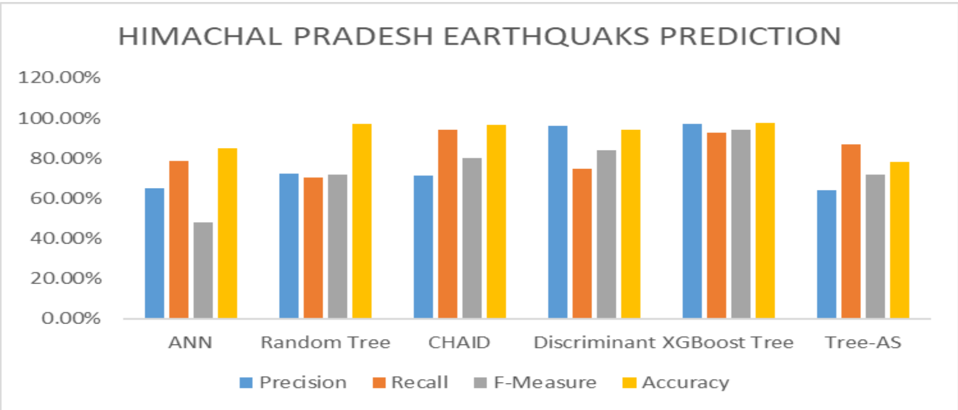

Figure 1. Comparison of classifiers' accuracy, precision, and recall as well as performance metrics

4.2 Result of Uttarakhand

The following is the prediction outcome for the Uttara Kand dataset: With 88.90% accuracy, Tree-AS was the most accurate. The precision and recall rate of Tree-AS are 82%. The performance and classification of the data set by several machine learning algorithms with varying performance parameters were shown in Figure 2.

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Research Article

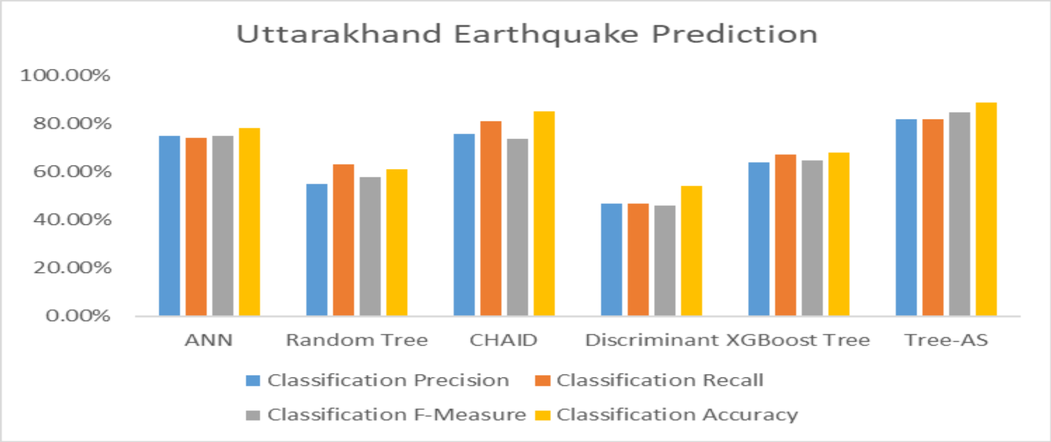

Figure 2: Performance and Classification of the Data Set By a Number of Machine Learning Algorithms

4.3 .Result of Nepal, UP & Bihar

The following is the prediction result for the UP dataset: With an accuracy of 98.90%, XGBoost Tree was the most accurate. The precision and recall rate of XG-Boost are 98.10%. Figure 3 showed the performance of various machine learning algorithms with varying performance parameters after the data set was identified**.**

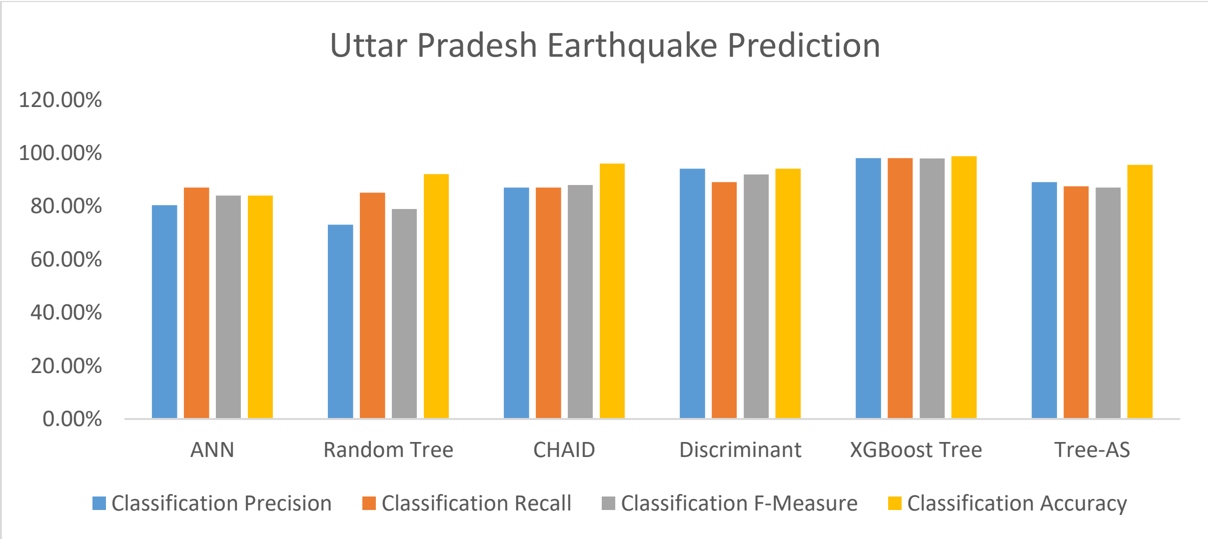

Figure 3. Comparison of Classifiers' Accuracy, Precision, and Recall

4.4. Result of North India

For the North India dataset, the Artificial Neural Network Tree yielded the best prediction results with an accuracy of 99.13%. XGBoost has a precision of 98.33% and a recall of 99.85%. The data set was identified in Figure 4, which also displayed the outcomes of several machine learning techniques with different performance measures.

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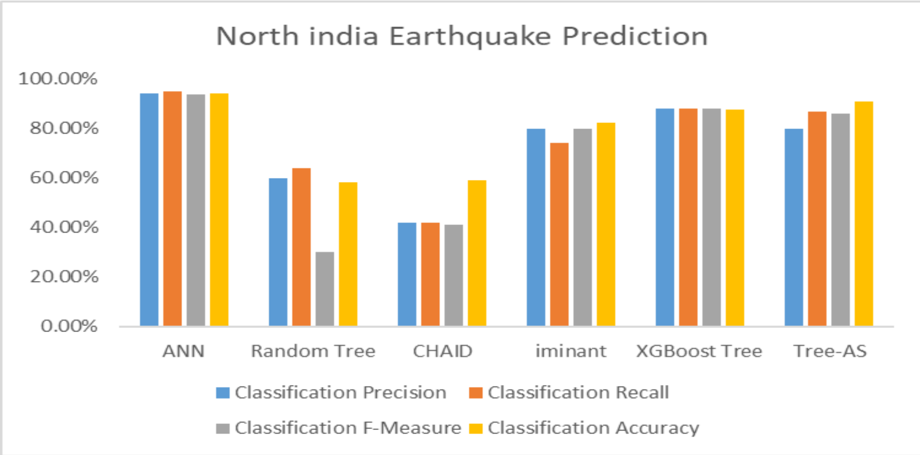

Figure 4. Comparison of Classifiers' Accuracy, Precision, and Recall

V. DISCUSSION

Every dataset was subjected to each of the six classifiers previously stated, and the results were documented. With the exception of the Gujarat earthquake dataset, XGBoost performed exceptionally well across all datasets. Artificial Neural Network and Tree-AS, in addition to XGBoost, demonstrated strong performance and provided the outcome for applying this model to forecast the impact of future earthquakes. Random trees and discriminants did not always perform adequately. Every classifier forecasts the magnitude of the earthquake. According to the results, the XGBoost classifier can be quite useful in predicting the earthquake's range. The primary goal of this study was to identify the type of earthquake so that the magnitude range could be determined.

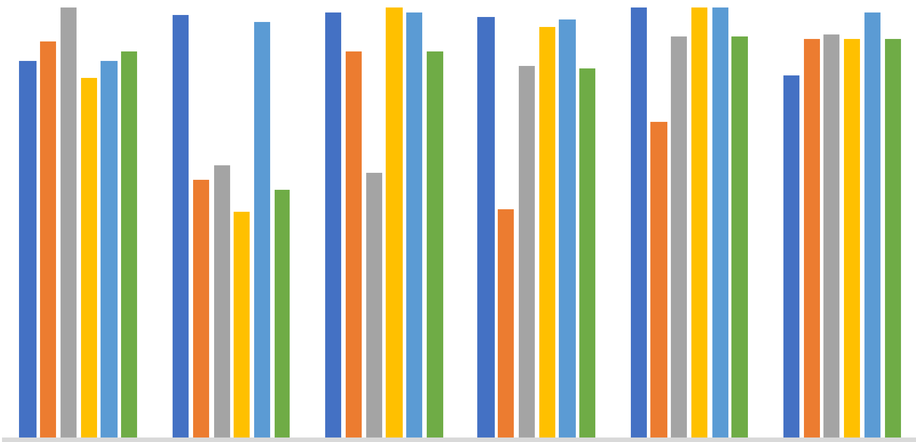

Figure 5. Comparison of Precision, Recall and Accuracy Of Classifiers

VI. CONCLUSION

Since earthquakes are among the most destructive natural disasters, it is important to identify them early on in order to prevent damage to the economy, infrastructure, and human life. When it comes to predicting earthquakes in India, machine learning can be extremely helpful. Using previously seismic datasets, an ML model has been developed to detect the magnitude range. A magnitude value is anticipated in this study.

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