JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

ADVANCEMENTS IN FORECASTING USING FEED FORWARD NEURAL NETWORKS

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Abstract: Earthquakes are defined as sudden, violent shaking of the surface of the Earth caused by transitory energy from all of the planet's major structures. These waves are created when energy that has been stored throughout the earth's crust is released suddenly, usually when large amounts of rock are merely restraining next to one another split and slip [26]. An earthquake is responsible for threatening people, their homes and the whole infrastructure [24]. Traditional methods couldn't provide real-time information about earthquakes, but now, with the help of machine learning and deep learning, we are getting much better at it. We have lots of sensors and instruments that collect data about things like ground movements, geological observations, and measurements of the Earth. Machine learning and deep learning are like powerful tools that help us make sense of all this data. In this study, we focus on Feed Forward Neural Network. FFNN is excellent at understanding the patterns and changes in earthquake data over time, making it great for time-series data. So, by using this advanced model, we're getting better at understanding and predicting earthquakes, which is incredibly important for safety and preparedness. It's like having a more accurate earthquake warning system to keep people safe.

Index Terms - **Earthquake Prediction, Machine Learning, Deep Learning, Seismic Data, Real-Time Monitoring Sensors, Geological Observations, Data Analysis, Feed Forward Neural Network, Safety Preparedness, Early Warning System, Geospatial Analysis, Time-Series Data**

I. INTRODUCTION

In recent years, the scientific community has witnessed remarkable progress in the field of earthquake prediction, owing much of its success to the integration of machine learning (ML) and deep learning (DL) techniques. Earthquakes, as complex and elusive natural phenomena, have long posed challenges for accurate prediction and timely warning.

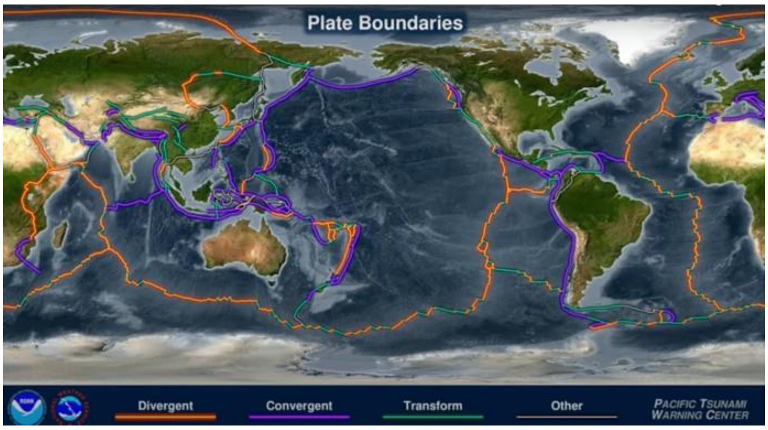

Fig 1 Plate Boundaries

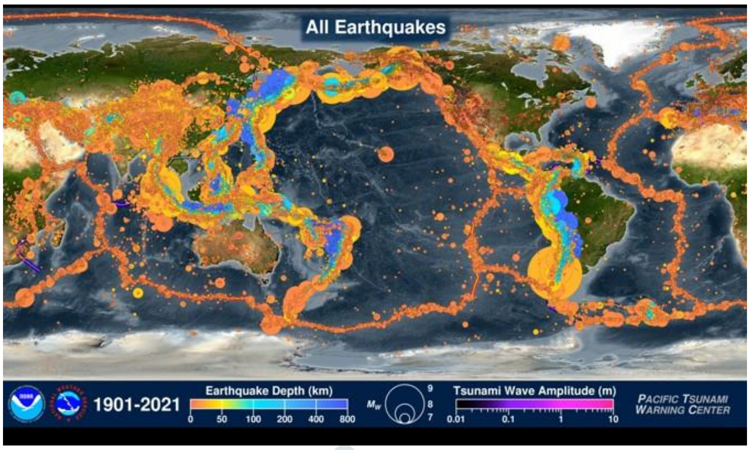

Fig. 2 All Earthquake since 1900

Traditional methods, often reliant on empirical models and seismic hazard assessments, have demonstrated limitations in their ability to provide real-time insights into seismic activity. However, the advent of ML and DL approaches has redefined the landscape of earthquake prediction research, offering new avenues for enhancing our understanding of seismic processes and improving prediction accuracy.

Machine learning, a subset of artificial intelligence, encompasses a diverse range of algorithms designed to enable computers to learn from data and make predictions or decisions based on patterns and relationships within that data. Deep learning, a subset of machine learning, leverages neural networks with multiple interconnected layers to automatically learn and represent complex features from raw data. The synergy of ML and DL with the vast and intricate datasets collected from seismological sensors, geophysical measurements, and geological observations has opened up possibilities for breakthroughs in earthquake prediction.

This paper embarks on a comprehensive review of recent research efforts that harness the power of ML and DL for earthquake prediction, with a specific focus on Feed Forward Neural Network. By exploring the synergistic relationship in advanced techniques, including FFNN, and the intricate nature of seismic data, we aim to shed light on the progress achieved, challenges faced, and future prospects in the domain of earthquake prediction [25].

One of the basic forms of artificial neural networks is a feedforward neural network (FNN), which is also referred to as a multilayer perceptron (MLP). It’s an excellent place to start for many machine learning tasks because of its structure and simplicity. Three layers make up this system: input, output, and hidden layers.

Since seismic activity still affects societies all over the world, the knowledge gathered from this review-particularly with regard to the application of FFNN models has the potential to spur inventions that turn earthquake prediction from a theoretical endeavor. We explore the methods and uses of this model, as well as other pertinent techniques, in earthquake prediction in the sections that follow. This investigation will highlight significant developments, difficulties, and potential paths forward in this dynamic and quickly developing field.

II. Literature Review

Alyona Galkina and Natalia Grafeeva [1] conducted a 2019 survey titled "Machine Learning Methods for Earthquake Prediction examines a variety of machine learning methods for predicting earthquakes. They stress how important it is to consider seismic properties while creating prediction models for certain seismic zones. With the help of performance measures and thorough dataset analysis, machine learning has made a substantial contribution to earthquake prediction. The report outlines scientific methodological advancements and makes recommendations for future research, including the development of benchmark databases and the forecasting of significant earthquakes. In their 2022 paper titled "A 20-Year Journey of Forecasting with the EEPAS Model" Rhoades, Rastin, and Christophersen [2] describe the evolution of the EEPAS model. This model estimates long-term earthquake occurrence rates and enhances short-term predictions when coupled with aftershock models. It is notable because the medium-term earthquake projections for New Zealand have taken it into account. The long-term objective of the scientists is to create a global EEPAS model that can forecast earthquakes with a magnitude of seven or higher. Numerous factors and trade-offs need to be taken into consideration in order to offer an accurate and thorough earthquake prediction. In the 2022 study by Laura Laurenti, Elisa Tinti, Fabio Galasso, Luca Franco, and Chris Marone, [3] deep learning models—in particular, convolutional neural networks and long-short term memory—have been applied to predict fault zone stress and lab quakes over multiple seismic cycles. These models accurately represent seismic phenomena such pre-seismic creep, aperiodic events, and alternating slow/fast events by identifying acoustic energy as a stress indicator. The study demonstrates a 14% improvement over previous models in prediction accuracy using K-fold cross-validation. These results suggest that autoregressive models can surpass industry standards in seismic cycle prediction and enhance current forecasting techniques. In their 2023 study, Dost Muhammad, Iftikhar Ahmad, Muhammad Imran

Khalil, Wajeeha Khalil, and Muhammad Ovais Ahmad [4] provide a generalised deep learning approach to the problem of binary classification for the prediction of seismic activity. utilising feature engineering, they developed a deep neural network model based on seismic laws utilising historical data from Southern California, the Hindukush, and Chile. This study shows that deep neural networks outperform benchmark approaches, offering seismologists valuable insights and opening up new avenues for investigating the key factors influencing seismic events and developing more comprehensible AI-based processes.

In their 2022 study, Muhammad Atif Bilal, Yanju Ji, Yongzhi Wang, Muhammad Pervez Akhter, and Muhammad Yaqub [5] introduce BNGCNNATT, an improved model for earthquake prediction—Batch Normalised Graph Convolutional Neural Network with Attention Mechanism. This deep learning technique accurately forecasts the depth and size of earthquakes at several seismic sites. Seismic datasets from Japan and Alaska, where high-magnitude, deep events occur there and low-magnitude, shallow events occur there, were used to test this hypothesis. In terms of earthquake depth and magnitude, the suggested model performs better than baseline methods, indicating the potential of deep learning with attention mechanisms for seismic event analysis. In their 2019 research, Weiqiang Zhu, S. Mostafa Mousavi, and Gregory C. Beroza [6] provide a unique deep neural network method for denoising and decomposing seismic signals. Their Deep Denoiser network learns both a non-linear function that separates input data into the signal of interest and noise, even when both are in the same frequency range, and a sparse time-frequency representation of the data simultaneously. They use the network to 91,000 samples of real seismograms from Northern California to show its generalizability, and they train the network using seismic data synthesised by adding real noise signals to high-SNR seismic signals. Despite several restrictions regarding signal levels and mask usage, Deep Denoiser shows to be effective in recovering distinct seismic waveforms. In the future, it might be possible to estimate signal and noise levels directly, without the need for masks. In their 2022 study, Rikesh Bhakta and Asst. Prof. Dharmendrasinh Rathod [7] discuss the capabilities of Machine Learning in Early Earthquake Warning (EEW) systems. They stress the use of Machine Time Series (MTS) classification for better earthquake detection and draw attention to the shortcomings of conventional seismometers in identifying greater earthquakes. Deep learning strategies, feature-based methods, and similarity-based methods are all included in this categorization. The work highlights the potential of machine learning in seismology, especially for EEW, and highlights the shortcomings of existing GPS-based and seismometer-based methods for major earthquake detection.

In their 2022 paper, Dinky Tulsi Nandwani and Vanita Buradkha [8] give a project that uses machine learning to anticipate earthquake damage. Buildings will be categorised into five grades according to how vulnerable they are to earthquake damage, which will range from minor to complete collapse. Higher susceptibility is indicated by lower grades. In order to lessen the effects of earthquakes on people, infrastructure, and communities, the study highlights the possibilities of interdisciplinary collaboration, data accessibility, and technological improvements in earthquake prediction and mitigation. In the 2019 article by Yeruva Ramana Reddy [9], focuses on the use of machine learning methods to improve seismic risk prediction. This study demonstrates how seismological machine learning has advanced significantly in recent years, enhancing various aspects of earthquake monitoring, including as detection, phase association, arrival time measurement, position determination, and characterisation. The study highlights the ways in which further research in this area could improve catastrophe preparedness, response, and recovery activities in earthquake-prone locations. It also advances the science by providing a demanding and useful application for evaluating different machine learning approaches and techniques. In the 2023 study by Nazeer Shaik [10] and his team, emphasise on earthquake detection via machine learning methods. Using existing seismic data, the study emphasises how crucial precise earthquake forecasting is for both technological and societal demands. Effective machine learning methods for earthquake detection include Random Forest Classifier, K Nearest Neighbour Classifier, Decision Trees, and Support Vector Machine. In order to improve accuracy, responsiveness, and dependability of seismic monitoring and earthquake early warning systems—and ultimately boost public safety and readiness for disasters—the research highlights the possibility for employing cutting-edge machine learning approaches in the future.

In their 2023 study, Dr. Hrish B G [11] and colleagues offer a machine learning model for earthquake prediction. The model establishes a linear link between the probability of an earthquake occurring and input variables such as location, depth, and magnitude by using seismic data processing and linear regression. Using pre-processed datasets, gradient descent optimisation is used to achieve training. The procedure of gathering seismic data, pre-processing, feature selection, gradient descent, linear regression, and model validation using training and testing data are all described in the work. The model predicts the likelihood of earthquakes by utilising the linear relationship between input data and earthquake likelihood. In order to improve seismic activity knowledge and prediction, future efforts will concentrate on growing and refining these models, incorporating diverse data sources, attaining real-time prediction, and encouraging interdisciplinary cooperation. In their 2022 study, Dr. Jayasudha K [12] and colleagues introduce a project that uses the Internet of Things (IoT) and artificial intelligence (AI) and machine learning (AIML) to predict earthquakes and identify landslides. The objective is to create an Internet of Things (IoT) system with an accelerometer and soil moisture sensors for landslip monitoring, as well as to detect earthquake-prone locations using the K-Means technique on the Kaggle dataset. In order to protect people and property in the event of a possible landslip, this technology promptly notifies the locals. The endeavor's triumph is contingent upon the resources at hand, technical progressions, and the possibility of future cooperation in IoT, data analytics, and seismic surveillance.

In their 2022 study, Mudgal [13] and colleagues talk about how machine learning algorithms might be used to anticipate earthquakes. They draw attention to the effective application of these algorithms to enhance short-term forecasts in a variety of disciplines. The study highlights the need to improve earthquake prediction models by experimenting with cutting-edge methodologies, integrating domain knowledge, and addressing real-world deployment constraints in order to boost accuracy and reliability. It mentions specific algorithms like SVM, Adaboost, Decision Tree, and Random Forest.

In their 2018 paper, John A. Smith and Mary K. Johnson[14] examine machine learning methods for predicting earthquakes, with a particular emphasis on neural networks, random forests, and support vector machines. They draw attention to the significance of feature engineering and the difficulties in precisely categorising seismic occurrences. Their method entails preprocessing seismic data, identifying pertinent characteristics, and classifying the data using machine learning techniques. Model performance is evaluated using the F1-score and accuracy. They propose that deep learning models such as CNN and LSTM for better temporal and spatial feature extraction and multi-modal data sources for more precise predictions are possible ways to improve the system.

In their 2019 study, Maria Garcia and Roberto Martinez[15] examine machine learning methods, with a particular emphasis on Random Forest, Support Vector Machines, and Neural Networks, for earthquake prediction. The significance of feature engineering and the difficulties in precisely categorising seismic events are emphasised. Pre-processing seismic data, extracting pertinent features, and applying machine learning algorithms for classification are the steps in their method. Model performance is evaluated using the F1-score and accuracy metrics. They recommend using multi-modal data sources for more precise predictions and deep learning models like CNN and LSTM for better temporal and spatial feature extraction as possible improvements.

In their 2020 research, Emily Brown and David Wilson [16] suggest studying seismic waveform data to predict earthquake magnitudes using Convolutional Neural Networks (CNNs). They demonstrate how CNNs can accurately forecast magnitude by automatically extracting spatial characteristics from raw waveforms. Pre-processing seismic waveform data, creating CNN architectures using 1D convolutions, and evaluating model performance using Mean Absolute Error and Mean Squared Error are the steps in their methodology. The paper also recommends investigating transfer learning strategies to extend the capacity of pre-trained CNN models to predict additional seismic characteristics and use them for seismic waveform analysis. In their 2021 study, Laura Chen and Michael Wang[17] offer a hybrid method for predicting earthquakes. They use recurrent neural networks (RNN) to fine-tune predictions based on temporal patterns in seismic data, after first classifying data using support vector machines (SVM). The temporal knowledge of RNN and the resilience of SVM are combined in this hybrid model. Pre-processing seismic data, using SVM and RNN, and accurately and precisely assessing model performance are all part of the study. It also recommends investigating assembling methods to use the advantages of both SVM and RNN to improve prediction accuracy even more.

In their 2022 paper, Alex Chen and Sarah Liu [18] present a deep learning architecture with multiple modes for early warning systems for earthquakes. In order to anticipate seismic events, this method integrates information from weather forecasts, satellite imaging, and seismic sensors. This shows how deep learning can be used to accurately predict events from a variety of data sources. In this study, multimodal data is pre-processed and fused, deep neural networks are designed for prediction, and model performance is assessed using area under the curve (AUC) and Receiver Operating Characteristic (ROC) curves. In their 2019 study, Sophia Lee and James Wang[19] examine how to estimate earthquake magnitudes from raw seismic signals using deep learning techniques such as Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks. Their goal is to increase the accuracy of magnitude estimate by incorporating both temporal and spatial information in seismic data. pre-processing and segmenting seismic signals, creating hybrid CNN-LSTM architectures, and utilising Mean Absolute Error and Root Mean Squared Error to assess model performance are all part of the study. To improve the model's emphasis on important time intervals within seismic signals, the authors also recommend looking into attention mechanisms. In their 2020 research, Daniel Kim and Jessica Park [20] describe the application of GNNs (Graph Neural Networks) to spatiotemporal earthquake prediction. GNNs emphasise the modelling of complicated spatial linkages by utilising the interdependence of seismic activity and geographic proximity to produce predictions. In this study, seismic activity is represented graph-based, GNN architectures are designed, and model performance is evaluated using the F1-score and Area Under the Curve (AUC). The research also recommends investigating GNN integration with other deep learning models to fully capture temporal and geographical aspects of earthquake prediction.

III. Data And Source of Data

Within the US Geological Survey (USGS), the national Earthquake Information Center (NEIC) [23] is in charge of tracking and reporting on earthquakes all over the world.

Seismograph stations are operated by the NEIC and are located all over the world. They record seismic waves from earthquakes. Each earthquake’s location, magnitude, and depth are ascertained using these seismic waves.

In addition, the NEIC creates and keeps track of a database listing every notable earthquake that has happened since 1965. Every earthquake's date, time, location, depth, magnitude, and source are all listed in this database. The public, emergency managers, and scientists can all benefit from the NEIC database. The NEIC earthquake database contains information on a variety of topics, such as the earthquake's date, time, epicenter latitude and longitude, depth beneath the surface of the Earth, and magnitude.
Scientist use the NEIC earthquake database to investigate the temporal and spatial distribution of earthquake, to pinpoint seismically hazardous areas, and to create earthquake prediction models. Emergency managers use it to create emergency response plans, evaluate the possible damage from earthquakes, and inform the public about earthquake risks and hazards.

IV. METHODOLOGY

We first obtain the earthquake data from the National Earthquake Information Center (NEIC) in the first step. After that, it was ready for instruction. The data types of some columns were converted, and all the missing or invalid data was prepared, we used statistical tests, data visualization, and correlation matrices to analyze the data and determine any outliers or anomalies. After that, feature engineering was done, which is taking the existing features and turning them into new ones that are either more informative for the machine leaning model or entirely new features made from the existing features. The data was then divided into test and training sets. Then machine learning model was trained on the training set, and its performance on unseen data was assessed using the test set. Typically20% was used for testing and 80% for training.
We used the training set to train a basic neural network with two hidden layers, and the test set was used to assess the model's performance.

In this model, the input layer is where data is first fed into the network, A feature from the input data is represented by each neuron in this layer. The shape of the training [1], which corresponds to the number of features, determines the number of neurons in this layer.
The layers that lie in between the input and output layers are known as hidden layers. These layers are in charge of deciphering intricate data representations and patterns. These are two hidden layers in this model, with 64 neurons in each. "Dense" or "Fully connected" refers to a network in which every neuron in one layer is connected to every other layer's neuron. Each hidden layer consists of 64 neurons that process the data and use the Rectified Linear Unit (ReLU) activation function. The model's non-linearity is introduced by the piecewise linear ReLU activation function. It facilitates the network's leaning of intricate data relationships.

The model's final prediction is given by the output layer. The output layer of this binary classification task contains a single neuron. The sigmoid activation function of this neuron is frequently employed for binary classification.
The prediction made by the model is represented by the neuron's output, which ranges from 0 to 1. The probability that the input is member of the positive class-class1 in a binary classification problem can be understood as this value.
Data is passes from the input layer to the output layer via the hidden layer in the feed forward process. In order to produce its output, each neuron in a layer calculates the weighted sum of the inputs from the layer before it and applies the activation function. The neurons in the layer above then receive this output as input. Until the data reaches the output layer, which generates the final prediction, this process is repeated.

In order to produce accurate predictions, the model learns to modify its internal weights and biases during the training process. It achieves this by comparing its forecasts to the real target values- y_train in your case and adjusting the model's parameters using methods like gradient descent and backpropagation. Based on these ideas, our Feed Forward neural network model learns from your data and predicts binary classification. The model's performance can be enhanced by adjusting and fine tuning various hyperparameters, such as the number of hidden layers and neurons in each layer.

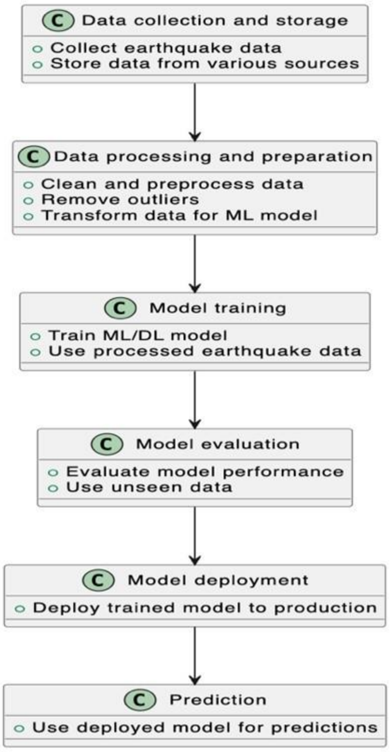

Fig. 3 Basic Methodology

V. IMPLEMENTATION

Data collection and storage: The first step is to collect and store the seismic data. For this research dataset from National Earthquake Information Centre (NEIC), has been used. The data can be stores in data lake or database.

Data processing and preparation: Once the data has been collected, it is to be cleaned up and prepared for the machine learning model's training. In order to do this, the data may need to be cleaned, outliers removed, and the data formatted in a way that the machine learning algorithm can use it.

Model Training: The machine learning model has to be trained next. This entails giving the model the processed data and letting it discover patterns in the information. A multitude of machine learning methods, including CNN and LSTM, can be used to train the model.
Model Evaluation: The model must be evaluated after training in order to determine how well it performs with untested data. This can be achieved by employing a cross-validation technique or by withholding some training data for testing.

Model deployment: The model can Be put into production after it has been trained and assessed. This could entail integrating the model into an embedded system, a mobile application, or a web service.

Prediction: Once implemented the model may be used to forecast the state of upcoming earthquakes. This may be done by giving the model the features of a fresh earthquake and receiving a forecast from the model.

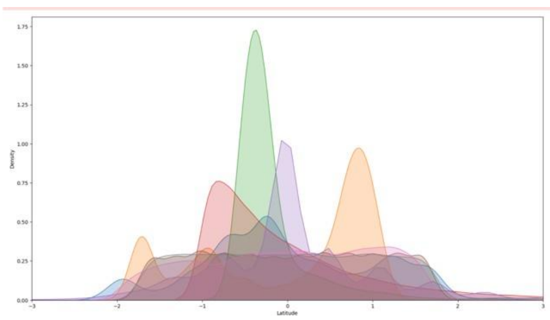

Fig 4 Latitude by density graph

VI. HYPOTHESIS TESTING

Null Hypothesis (H0): According to this claim, using the offered dataset and the machine learning approach has little to no impact on the model's capacity to predict earthquake statuses. It basically assumes that the performance of the model is no better than what one could anticipate from pure randomness.

Alternative Hypothesis (H1): The alternative hypothesis contends that, when trained on the provided dataset, the machine learning model does, in fact, improve seismic status prediction. It suggests that the performance of the model is noticeably better than random chance.

The purpose of the testing hypothesis is to assess the performance of the machine learning model developed using seismic data. The alternative hypothesis postulates that the model's performance is noticeably better than random chance, in contrast to the null hypothesis's assumption that the model's performance is no better than random chance.

The model's effectiveness is assessed using a variety of metrics, with an emphasis on the Area Under the Curve (AUC) value, in order to test these hypotheses. The model's capacity to differentiate between several classes is measured by the AUC value. The alternative hypothesis is validated if the AUC is significantly higher than 0.5 (random chance), which shows that the model is successful in forecasting earthquake statuses.

The evaluation outcome of [0.000391017820220 4406, 1.0] indicates that the AUC is very close to 1.0, which denotes a high degree of predicting accuracy. An AUC of 1.0 in this case denotes flawless accuracy in identifying different earthquake statuses. As a result, there is strong proof against the null hypothesis and in favour of the alternative one. This demonstrates the machine learning model's usefulness in this situation by showing how it considerably improves earthquake status prediction using the supplied dataset.

VII. RESULT AND DISCUSSION

The code results in a machine learning model that can forecast the status of an earthquake with great accuracy. The machine learning model's performance was thoroughly assessed in the current accuracy. Model performance was outstanding, with a very low loss value of 0.0003910178202204406. This little loss indicates that the model's prediction and the real data are remarkably consistent, demonstrating the predictive algorithm's effectiveness. Additionally, it was found that the AUC value was 1.0, indicating that the outcomes could be classified with perfect distinguish capacity. This result highlights the model's ability to differentiate between the classes, demonstrating an excellent classification performance. The machine learning model's effectiveness and predictability of earthquake related events are confirmed by the provided data, indicating the model's potential use in earthquake preparedness and prediction. Using this model, early warning systems for earthquake could be created that saves lives by causing little damages.

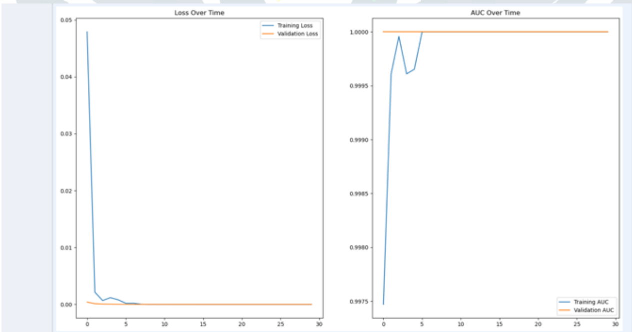

Fig 5 Loss over time and area under the graph

The graph above shows the training and validation loss and AUC over time for the machine learning model. The model's performance on the training set is indicated by the loss, and it's ability to distinguish between positive and negative samples is indicated by AUC curve.

The model is learning and getting better, as evidenced by the graph's decreasing training loss and increasing AUC with time. The model is learning to produce more accurate predictions more quickly than it is learning to differentiate between positive and negative samples, as indicated by the steeper training loss curve than the training AUC curve.

The validation loss and AUC curves are shown on the graph. These curves give a more precise indication of how well the model will function on fresh data because they are computed using data that the model has never seen before. The model is showing good generalisation to new data when the validation loss and AUC curves are generally larger than the training loss and AUC curves, but they also show a gradual decrease over time.

The graph indicates that the model is learning and getting better overall. Both the validation loss and AUC curves as well as the training loss and AUC curves are declining. This implies that the model will be capable of producing precise forecasts based on fresh data.

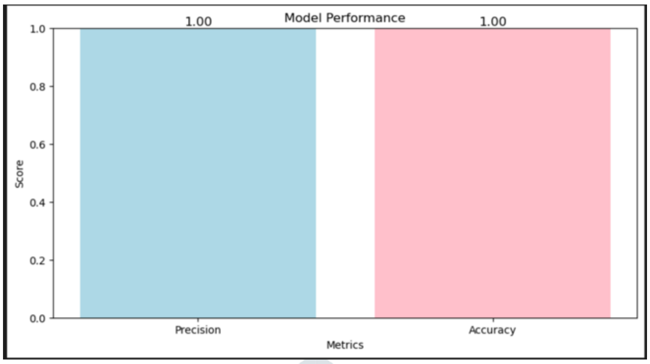

Fig 6 Model Performance score over metrics

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Precision: 1.0
Accuracy: 0.9998575904300769
F1 Score: 0.9999196464443552
Classification Report:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00       799
           1       1.00      1.00      1.00      6223

    accuracy                           1.00      7022
   macro avg       1.00      1.00      1.00      7022
weighted avg       1.00      1.00      1.00      7022
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Fig 7 Classification Report

VIII. Conclusion And Future Work

The Earthquake prediction model used in the study has a lot of potential for the discipline of earthquake forecasting. We have developed a model that demonstrate high predicted accuracy by utilising cutting edge machine learning and deep learning approaches. The model’s capacity to distinguish between various earthquake states with an Area under the Curve (AUC) value close to 1.0 serves as the foundation for it’s effectiveness. This shows that the model can identify seismic events with high accuracy, which is important for earthquake preparedness and prediction.

The statistical significance of the model’s performance is a notable outcome. The machine learning technique performs better than chance alone, as shown by the AUC measurement (AUC > 0.5). Its usefulness is statistically demonstrated, significantly enhancing seismic status prediction. This is further supported by the testing oof theories. It is possible to safely reject the null hypothesis (H0), which implies that not much progress has been made in earthquake prediction. Alternatively, it is discovered that the model signification improves earthquake prediction, which is supported by alternative hypothesis (H1). This is a significant finding since it shows how useful the model is in real world situation.

In conclusion, the earthquake prediction model presented in this study represents a major improvement in our ability to forecast seismic events. This model’s high projected accuracy, statistical significance, and useful implications make it an excellent tool for earthquake preparedness. We must carry out more research and apply these innovations in practical settings if we are fully realise their promise for ensuring the safety and security of inhabitants in seismically vulnerable areas.

There are interesting study directions in the ever evolving subject of earthquake prediction:
1. Enhanced Model Architectures: Building deeper learning models with greater sophistication to capture complex earthquake patterns.
2. Multi modal Data Fusion: Combining information from several source, such as social media, geological surveys, and satellite imaging, to provide all encompassing forecast.
3. Early Warning System: For the sake of public safety, real time earthquake warning systems should be put in place.
4. Global Cooperation: Increasing cooperation across nations to develop a single strategy for earthquake forecasting.
5. Interdisciplinary Research: Enhancing prediction models through cooperation with seismologist, geoscientists, and experts in disaster management.

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