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REVIEW ARTICLE

AI for Earthquake Prediction: A Comparative Analysis of Machine Learning Techniques in Natural Disaster

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Abstract—**Earthquakes are complex natural disasters that may significantly impact people's well-being, their possessions, and the natural world. Inaccurate estimates of earthquake time, location, and magnitude are common since earthquakes do not follow any particular patterns. The capacity of AI-based techniques to uncover previously unseen patterns in data has made them famous. This research presents an AI-driven method for earthquake prediction using the Gated Recurrent Unit (GRU) model and historical seismic data from the USGS. After the data is prepared, features are chosen, and the model is trained, the accuracy, precision, recall, and F1-score are used to assess the performance. The GRU model outperforms Logistic Regression (LR), Recurrent Neural Networks (RNN), and Artificial Neural Networks (ANN) in a comparative comparison. It successfully achieves an accuracy of 93.10% while minimizing overfitting. The results highlight the effectiveness of GRU in capturing temporal dependencies in seismic events. However, challenges such as data imbalance, computational complexity, and regional generalization remain. Future research should focus on integrating additional geological and environmental parameters, optimizing computational efficiency, and developing real-time predictive frameworks to enhance the reliability of AI-driven earthquake forecasting.**

Keywords—***Environment, Natural Disasters, Earthquake Prediction, Machine Learning, Earthquake Forecasting, Early Warning Systems, Disaster Risk Reduction, Machine learning.***

Introduction

The environment is vital to life on Earth because it provides us with air, water, and land, which are all necessities for survival. However, natural processes and human activities often lead to environmental changes that can have both short-term and long-term consequences. Among these natural processes, extreme events such as hurricanes, floods, wildfires, and earthquakes pose significant threats to human civilization [1]. As a whole, these calamities are known as natural disasters, and they often leave impacted areas devastated and economically crippled for years. One of the most destructive types of natural catastrophes is an earthquake[2]. Earthquakes emerge without prior indications which forces people to react with minimal preparation time [3]. These seismic events produce ground movements that activate accompanying secondary risks, including tsunami waves and landslides, that increase the overall damage magnitude [4][5]. Scientific research into predicting earthquakes represents an ongoing challenge because earthquakes behave unpredictably.

Traditional examination of earthquakes depends on geological and historical data for potential seismic occurrence predictions [6][7]. These procedures can be classified as either short-term or long-term. In particular, the evacuation procedure benefits from the short-term method, which forecasts the possibility of an earthquake a few days or weeks in advance. The methodologies offer beneficial understanding but do not supply sufficient accuracy for present hazard identification. A viable substitute has evolved in the form of ML methods in the last several years. By processing seabeds data, the algorithms can map out patterns, and the likelihood of abnormalities in the probability of earthquakes and seismic activities [8]. To be sure, conventional methodologies have not been employed in seismic hazard assessment or monitoring in recent times due to their ineffectiveness. The above-discussed approaches in coupling AI solutions have the potential to transform earthquake forecasting [9], yielding quicker and more accurate prediction information to reduce effects of the disaster [10].

This study, therefore, seeks to explore how machine learning approaches can be utilized in earthquake prediction, compared to other approaches that apply in natural disaster prediction. It discusses various models and their merits and demerits, and makes a comparative analysis to evaluate the possibility of AI ramping up the level of disaster preparedness and response.

Motivation and Contribution of the Study

Earthquakes remain among the prominent natural disasters whereby several lives are lost, adequate amounts of money are spent, and infrastructures are brought down. The complexity and non-stationary nature of seismic behavior make the probability of accurate prediction of earthquakes a noteworthy problem in seismology even at the present stage. Most of the traditional statistical models are incapable of addressing complex temporal as well as spatial dependencies; therefore, resorting to elaborate AI methods is unavoidable. ML and DL methods have shown promising results in predictive analytics, making them viable tools for earthquake forecasting. This study uses a massive dataset from the USGS to conduct an exhaustive comparison of several ML models for earthquake prediction. The key contributions of this study include:

- Utilized the USGS dataset with over 4 million seismic data entries for analysis.
- Employed data cleaning techniques, including the removal of columns with excessive missing values.
- Engineered derived characteristics, which provide light on seismic patterns; for example, the time intervals between sequential earthquakes of varying magnitudes.
- Evaluating and comparing the performance of multiple ML algorithms (LR, RNN, ANN and GRU.) in predicting seismic events.
- Model efficacy is evaluated using measures such as accuracy, precision, recall, loss, and F1score, which provide a data-driven rating of various AI approaches.

Justification and Novelty

This work provides evidence that DL and ML approaches can improve earthquake prediction over standard statistical models by better representing the complex and nonlinear characteristics of seismic activity. Leveraging a comprehensive USGS dataset (1904–2023), the research implements a strong pipeline for preparing data that includes feature selection and management of missing values to improve model reliability. A key novelty of this study is the introduction of interoccurrence time intervals as a derived feature, providing deeper insights into seismic patterns. Additionally, the study conducts a comparative analysis of multiple ML models, assessing their effectiveness in predicting earthquake occurrences based on key seismic parameters. By integrating a data-driven approach with rigorous model evaluation metrics (F1score, recall, accuracy, and precision), this research offers a benchmark study in AI-driven earthquake forecasting, contributing to improved disaster preparedness and early warning systems.

Structure of Paper

The structure of the paper is as follows: Section II reviews previous studies on the use of artificial intelligence for predicting natural disasters. Section III outlines the methods and procedures employed in this study. Section IV analyses the results obtained. Finally, Section V summarizes the findings of the study and proposes future research directions.

Literature Review

This section presents their earlier work on earthquake detection with new technology and then contrasts it with other relevant research projects. Table I summarizes key methodologies, performance metrics, datasets, and future research directions from recent studies on natural disaster prediction and management.

Bhatia, Ahanger and Manocha (2023) propose an intelligent system for earthquake monitoring and prediction using cloud and edge computing based on collaborative IoT. The classification performance was superior with 92.52% precision, 91.72% sensitivity, and 91.01% specificity, as measured by the experimental simulation, is achieved by the proposed framework. Furthermore, the results demonstrate that using edge computing considerably decreases computational latency, which is 23.06s. As an added bonus, the offered model achieves better accuracy and throughput with stability at 92.16% and dependability at 95.26% [11].

Wang, Li and Qu (2023) introduces a method that uses machine learning (ML) to forecast the collapse condition of RC columns that have been damaged by an earthquake and will be subjected to other earthquakes. The outcomes of these numerical analysis models applied to one thousand ground motion records allow for the construction of a dataset based on time history analysis. AUC score of 0.87 and F1 measure of 0.76 show that the prediction model is quite accurate [12].

Pyakurel, Dahal and Gautam (2023) used landslide polygons to create 23,217 points that were landslides and 23,213 points that were non-landslides. The findings showed that LR had an accuracy of 74.40% and ET of 86.60%. Within the range of 0.866 to The area under the ROC curve for five machine learning algorithms is 0.744 for true label prediction and 0.935 to 0.819 for probabilistic prediction [13].

Banna et al. (2021) creates a model for predicting when and where earthquakes may occur. LSTM is recommended for the model's construction due to its memory-keeping capabilities, according to the literature assessment. An attention mechanism was included into the LSTM architecture, which increased the model's acc-uracy in earthquake prediction to 74.67% [14].

Kollam and Joshi (2020) use the Computing Unified Device Architecture (CUDA) framework, a well-known programming paradigm for General-Purpose Computing on GPU, in the creation of a PSVR employing a GPU. They offer a GPU-based PSVR model for earthquake prediction. When tested on the CPU and GPU, this recently computed PSVR model outperformed Scikit Learn and LibSVM libraries in terms of training speed and accuracy, reaching 92% [15].

Existing studies in earthquake prediction face challenges in accuracy, real-time processing, and interpretability. Many models, such as LSTM and PSVR, require high computational resources or struggle with sequential data. Additionally, limited explain ability hinders practical adoption. To address these gaps, this study proposes a GRU-based model that efficiently captures temporal dependencies with high accuracy and minimal overfitting. This approach bridges the gap between accuracy, efficiency, and reliability in AI-driven earthquake prediction

TABLE I. SUMMARY OF THE PRIOR RESEARCH ON EARTHQUAKE DETECTION AND PREDICTION USING ML APPROACH

Author	Dataset	Approach	Performance	Limitations & Future Work
Bhatia, Ahanger, and Manocha (2023)	Real-time IoT sensor data	IoT-Edge framework with Bayesian models and ANFIS for earthquake prediction.	Precision: 92.52%, Reliability: 95.26%,	Extend to other disasters and optimize computation.
Wang, Li, and Qu (2023)	10,000 RC Column Models, 47 PEER RC Columns	ML-based collapse prediction using Random Forest (RF) & SHAP explanations	AUC: 0.87, F1 Score: 0.76	Enhance dataset diversity and refine feature selection for higher accuracy
Pyakurel, Dahal, and Gautam (2023)	Landslide Polygons and Earthquake Data (23,217 landslide, 23,213 non-landslide points)	Ensemble Learning (ET, LR) with SHAP analysis	ET Accuracy: 86.60%, AUC: 0.866	Explore deep learning for improved landslide prediction and integrate real-time monitoring

Banna et al. (2021)	Bangladesh Earthquake Catalog.	LSTM with attention mechanism	Accuracy: 74.67%	Test other architectures on larger datasets.
Kollam and Joshi (2020)	Earthquake datasets processed on GPU.	Parallel SVR	Accuracy: 92%	Optimize for large datasets and compare with DL models.

Methodology

This study on AI for Earthquake Prediction using Machine Learning employs a structured methodology encompassing the process of gathering data, cleaning it up, analysing it, selecting features, and training the model. The dataset is derived from the USGS and covers the years 1904–2023, and contains over 4 million earthquake records. To increase model performance, the data is preprocessed by removing unnecessary columns, normalizing the data, and addressing missing values by mode imputation. Feature selection focuses on key seismic parameters such as magnitude, depth, location coordinates, and interoccurrence time intervals to enhance predictive modeling. The dataset is divided into training (70%) and testing (30%) sets in order to assess several machine learning models, such as ANN, GRU, RNN, and LR. The comparison study evaluates these models' performance according to F1score, recall, accuracy, and precision, offering valuable information about how well AI-driven earthquake prediction methods work. In Figure 1, the approach used in this study is clearly depicted.

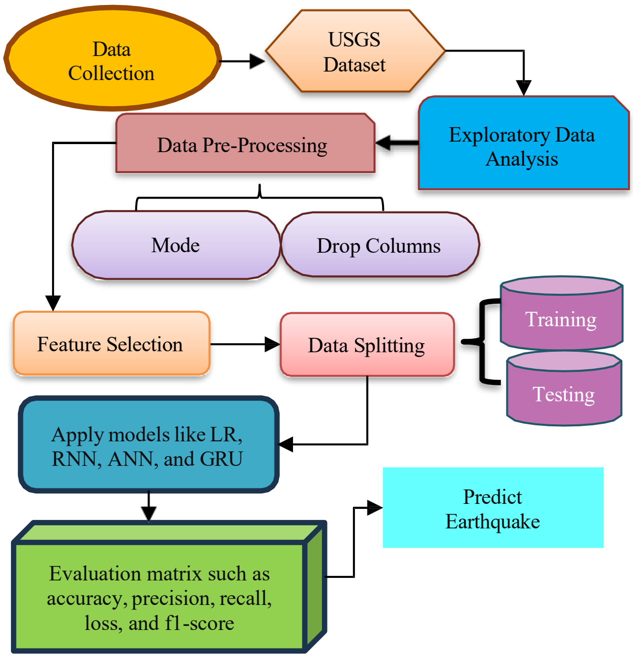

Fig. 1. Flowchart for earthquake prediction

Below is a description of the general procedure that is involved in the in-depth investigation of the data flow diagram:

Data Collection

The US Geological Survey provided the data used in this research. Data about earthquakes throughout the world from 1904 to 2023 is available in the US Geological Survey dataset. Seismographs and other monitoring stations documented important features and patterns of seismic activity in this dataset, which has 22 columns with 4,036,902 unique elements.

Exploratory Data Analysis

EDA plays a crucial role as the first step in the knowledge discovery process. This iterative process allows them to uncover patterns, anomalies, and insights that would otherwise remain hidden [16]. In the context of this study, they conducted a comprehensive data visualization on the USGS dataset, which illustrates their findings and analytical approach in detail, as presented below:

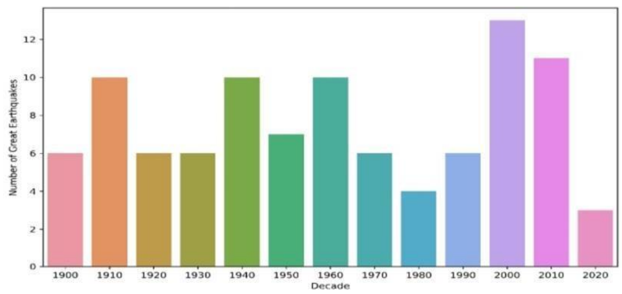

Fig. 2. Bar Graph for Decadal Trend of Earthquakes

In Figure 2, the number of earthquakes of a magnitude of eight or higher is displayed for each decade beginning in 1900 and continuing until 2020. According to the statistics, there have been oscillations throughout the course of time, with a significant increase occurring in the 2000s, followed by a reduction in the 2010s.

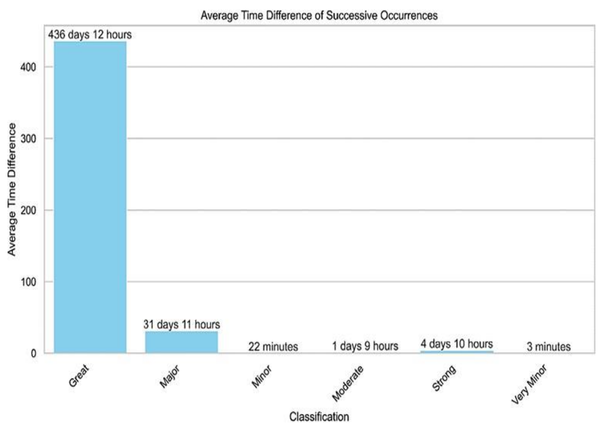

Fig. 3. Average time difference between successive occurrences

Figure 3 represents the categorization of earthquakes, which illustrates the average amount of time that passes between subsequent earthquake activity. When compared to "Very Minor" earthquakes, which occur relatively often with an average gap of just three minutes between events, "Great" earthquakes have the greatest average time difference, which is 436 days.

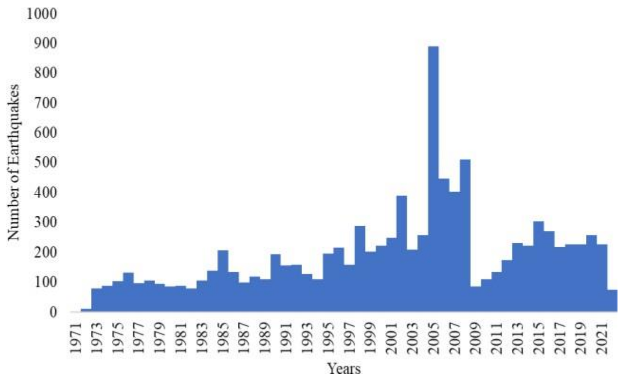

Fig. 4. Frequency of earthquake occurrence per year

The bar graph the yearly frequency of earthquakes from 1971 to 2021 is shown in Figure 4. Years are shown on an x-axis, while the number of reported earthquakes is shown on a y-axis. The data reveals a fluctuating trend in earthquake occurrences, with a notable increase after the 1990s, peaking significantly around the early 2000s, particularly in 2004. Following this peak, the frequency exhibits periodic variations, with occasional surges in earthquake activity. This visualization highlights temporal trends in seismic activity, which could be useful for understanding patterns and improving earthquake prediction models.

Data Preprocessing

Data preprocessing stages have a direct relation to the reliability and the quality of the datasets [17]. The process of data cleaning alongside transformation and organization enhances raw data suitability for analysis when applied through proper data management methods. The researchers applied multiple preprocessing strategies through standard scaling normalization and shape checks and null value detection on their dataset. Further preprocessing steps are discussed below.

- **Dropping Columns:** The analysis may lose analytical significance due to columns containing extremely high numbers of missing values ('nst', 'gap', 'din', 'rms', 'horizontal Error', 'depth Error', 'maguro', 'magnate'). They may remove them from the dataset to make it more efficient and less biased since there are more than a million missing values.
- **Mode Imputation:** Fill missing values with the most frequently occurring magnitude type.

Feature Selection

The raw earthquake data is sorted by important criteria including magnitude, depth, time of occurrence, geographical coordinates, and so on. The analysis of derived characteristics helps understand seismic behavior through calculations of time intervals between earthquakes that range in magnitude. A more thorough comprehension of earthquake patterns and trends on a worldwide scale is made possible by using these constructed features as input variables for statistical, interoccurrence time, and spatiotemporal analysis.

Data Splitting

This research utilizes a complete dataset that divided training purposes into 70% and reserved 30% for the testing phase. The training phase took place using the training dataset before performing testing operations with the testing dataset.

Proposed Gated Recurrent Unit (GRU)

The GRU is a type of RNN designed for processing sequential data. Memory blocks in a cell are not present in GRUs, in contrast to conventional RNNs[18]. A Gruel consists of two primary components: an update gate and a reset gate. The reset gate uses the sigmoid activation function (σ) to decide how much of the past should be forgotten, which outputs r_t. If r_t is 1, data is passed through; if 0, it's not. The update gate finds out what data to save for the future by using the same sigmoid function that gives us z_t. This output is combined with a tanh function (ranging from -1 to 1) to create a new cell state, $\hbar_t$. Last but not least, the hidden state output h_t is created by adding this new state to the current cell state [19]. The mathematical representation of the GRU operation is given below Equations (1-4):

Reset Gate

$$r_t = \sigma(W_r x_t + U_r h_{t-1} + b_r) \qquad (1)$$

Where, r_t: regulates how much of the past should be forgotten. σ: Sigmoid activation (output range: 0 to 1). W_r, U_r, b_r Weights and bias for input x_t and previous hidden state h_{t-1}:

Update Gate

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \qquad (2)$$

Where, z_t Controls how much past and new information to combine. W_z, U_z, b_z Weights and bias for input and hidden state.

Candidate Hidden State

$$\hbar_t = \tanh(W_h x_t + U_h (r_t . h_{t-1}) + b_h) \qquad (3)$$

Where $\hbar_t$ New candidate for the current hiddenstate. tanh Activation function (output range: -1 to 1). $r_t . h_{t-1}$ Element-wise product to selectively use past hidden state.

Final Hidden State

$$h_t = z_t . h_{t-1} + (1 - z_t) . \hbar_t \qquad (4)$$

Where, h_t Final output of the GRUcell. Combines the retained past state $z_t . h_{t-1}$ with the new candidate $(1 - z_t) . \hbar_t$

Model Evaluation

The model evaluation assesses a performance of models on new data [20]. The research employs accuracy, precision, recall as well as F1-score metrics to perform a thorough performance evaluation [21].

Accuracy: This statistic expresses the forecast accuracy as a percentage. Equation (5) provides the accuracy calculation formula.

$$Accuracy = \frac{TP+TN}{TP+TN+FN+FP} \qquad (5)$$

where TP stands for "true positive," meaning the model's prediction of the earthquake was accurate. There was no earthquake and the model did not forecast it, as indicated by the TN (true negative) value. False positives (FP) indicate that an earthquake did not occur, but the model predicted it; false negatives (FN) indicate that an earthquake did occur, but the model failed to forecast it.

Recall: It is the percentage of predictions that were accurate for the given set of cases. Recall may be calculated using the formula in Equation (6).

$$Recall = \frac{TP}{TP+FN} \tag{6}$$

Precision: This metric measures how often out of every possible instance are projected to be of a specific class. Equation (7) represents the formula for calculating precision.

$$Precision = \frac{TP}{TP+FP} \tag{7}$$

F1-Score: The F1-score may be defined as the precision and recall harmonic mean. The formula for computing the F1-score is given by Equation (8).

$$F1 - Score = \frac{2 \times precision \times recall}{precision \times recall} \tag{8}$$

Loss: Loss quantifies how far a model's predictions are from the actual values. It is an optimization metric used during training, with lower values indicating better performance.

Result Analysis And Discussion

The systems that were used for each implementation were Windows 10 64-bit PCs with 16 GB of RAM and 2 CPU cores. The experimental outcomes of the suggested GRU model, which evaluates the performance matrix encompassing f1score, recall, precision, accuracy, and loss, are shown in Table II.

TABLE II. FINDINGS OF THE GRU MODEL ON THE USGS DATASET FOR EARTHQUAKE PREDICTION

Performance Matrix	Gated Recurrent Unit (GRU)
Accuracy	93.10
Precision	93.20
Recall	93.17
F1-score	93.17

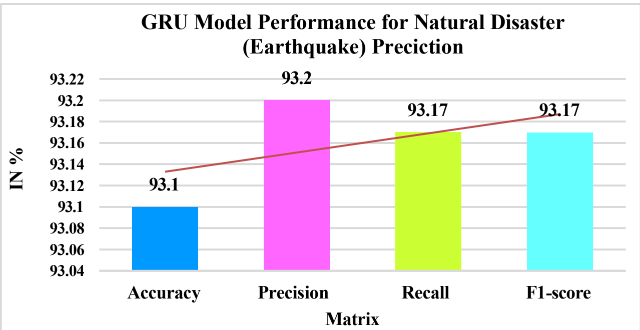

Fig. 5. Bar graph for GRU Model Performance

Table II and Figure 5 show the GRU model's performance. In this figure, GRU model delivers 93.10% accuracy alongside precision and recall values of 93.20% and 93.17%, which results in an F1-score of 93.17%. The performance metrics demonstrate the GRU model's success in handling sequential data from earthquakes while delivering stable and dependable outcomes with practically no trade-offs between observation quality and recall rate.

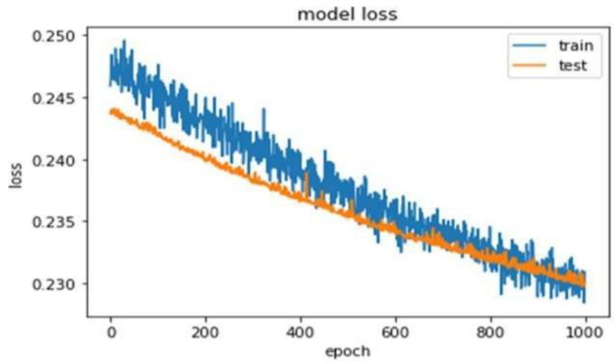

Fig. 6. Training and Testing Loss for GRU

Figure 6 illustrates the model's loss curves for training and testing over 1000 epochs. The downward slopes observed in both curves confirm that model performance improves continuously during the training process. The model demonstrates strong generalization abilities because training loss tracks closely with the testing loss, which prevents unwanted overfitting.

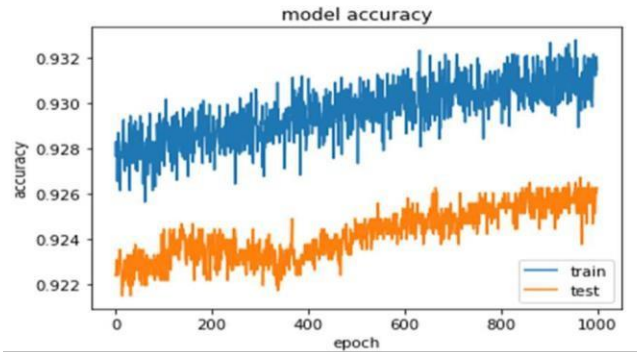

Fig. 7. Training and Testing Accuracy for GRU

Figure 7 shows the accuracy curves for testing and training across 1000 epochs. A blue line displays training accuracy, while an orange line shows testing accuracy. Both increase over time, with training accuracy (0.926–0.932) slightly higher than testing accuracy (0.922–0.926), indicating mild overfitting. Despite fluctuations, both follow a general upward trend, with rapid gains in early epochs that gradually stabilize.

Comparison and Discussion

This section evaluates the model's performance against existing model performance on the same dataset. The GRU model that follows is contrasted with examples of current models, including LR [22], RNN [23] and ANN [24] that trained on the USGS data, as shown in Table III.

TABLE III. COMPARISON BETWEEN GRU AND EXISTING MODELS' PERFORMANCE ON THE USGS DATASET

Models	Accuracy	Precision	Recall	F1-score
LR[22]	80.65	81.70	80.70	81.0
RNN[23]	83.3	-	-	-
ANN[24]	90.84	91.03	92.27	91.65
GRU	93.10	93.20	93.17	93.17

Table III compares the performance of GRU with existing models on the USGS dataset. The GRU model outperforms all other approaches, achieving the highest accuracy (93.10%), precision (93.20%), recall (93.17%), and F1-score (93.17%). In contrast, the ANN model follows closely with 90.84% accuracy, 91.03% precision, and 91.65% F1-score, demonstrating strong predictive capability. The RNN model reaches 83.3% accuracy without sharing any F1-score outcomes, recall, and precision. With an F1-score of 81.0 and accuracy and precision of 80.65% and 81.70%, respectively, the LR model exhibits the lowest performance. The superior results of GRU demonstrations establish its superiority for detecting earthquakes which indicates its suitability as a preferred method for this task.

A proposed model using GRU architecture delivers enhanced earthquake prediction in comparison to classical approaches because it provides better accuracy as well as proficient sequential data processing and expanded prediction capabilities. The GRU model reaches a 93.10% accuracy in predicting earthquakes which proves its ability to extract temporal elements from seismic data. GRU processes sequence of earthquake data to have less computational complexity than models which comprises of LSTMs, and are generally problematic for long term dependency. The model demonstrates low sensitivity to overfitting issues based on its training and testing loss curves' alignment which indicates its reliability for practical use. These successes are possible due to the improvement of feature selection and the increased efficiency of the models using the GRU for seismic forecasting in order to reduce disaster risks.

Conclusion And Future Scope

Earthquakes are a complicated and prolonged natural phenomenon or event that impacts the lives of people and their structures, including the environment. The determination of when the earthquake will occur and the most likely location and magnitude is still a real problem in seismology since earthquakes demonstrate irregular patterns that cause uncertainty for forecast models. This paper makes the case as to how ML techniques can be utilized for earthquake prediction, especially when employing the GRU model. Compared with classical models such as LR, RNN, and ANN, evaluation metrics consisting of maximum accuracy, precision, recall, and F1score prove the superiority of the GRU model. The results of the experiments show that the suggested GRU model is dependable in processing sequential earthquake data with an accuracy rate of 93.10%, thus, it can be relied upon for earthquake prediction. The model shows good non-specificity and low levels of overfitting that are impressive for seismic event prediction. Additional challenges exist regarding unbalanced data, along with the focus on minimal seismic indicators and calculation expenses, and generalization problems between regions. Future research demands work in three areas: adding more environmental elements into the model framework while balancing model classes more effectively while enhancing operational speed, and testing the model across different geologic regions.

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