Earthquake Prediction System

AI & DS Project
Report Group: 7

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Abstract

In today's world, predicting natural disasters like earthquakes has become critical for minimizing damage and saving lives. This project presents an advanced Earthquake Prediction System, leveraging both Machine Learning (ML) and Deep Learning (DL) techniques for enhanced prediction accuracy.
The system integrates traditional algorithms like Random Forests and XGBoost with advanced architectures such as LSTM, Transformers, and Autoencoders to forecast earthquake magnitudes and classify severity levels based on geospatial features like latitude, longitude, and depth.
Additionally, interactive tools like Gradio and Streamlit are used for building user-friendly web interfaces, while technologies like SHAP explain model decisions, promoting transparency. Extensive feature engineering, model stacking, hyperparameter optimization (using Optuna), and uncertainty quantification methods have been applied to strengthen the system’s robustness.
Comparative analysis with traditional prediction models highlights significant improvements in precision, recall, and early detection capabilities. The solution provides a scalable, interpretable, and real-time earthquake monitoring tool to aid governments, researchers, and rescue organizations in proactive decision-making.

Keywords: Earthquake prediction, Machine Learning, Deep Learning, LSTM, XGBoost, Transformers, Feature Engineering, Gradio, Streamlit, SHAP, Model Stacking, Uncertainty Quantification, Hyperparameter Optimization.

Introduction

In an era where natural disasters continue to pose severe threats to life and infrastructure, accurate and timely earthquake prediction has become a global necessity. Traditional seismic monitoring systems often rely on physical sensors and post-event analysis, which can be reactive and insufficient for large-scale disaster preparedness. To overcome these limitations, the integration of Machine Learning (ML), Deep Learning (DL), and Artificial Intelligence (AI) techniques offers a transformative approach to predicting earthquake magnitudes and severity with higher precision and speed.

The core challenge in earthquake forecasting lies in modeling the complex patterns hidden in geospatial and seismic data. Attributes like latitude, longitude, depth, and temporal sequences can reveal crucial insights, but manual analysis is time-consuming and prone to inaccuracies. By leveraging predictive models such as Random Forests, XGBoost, LSTMs, Transformers, and Autoencoders, we aim to automate and enhance the accuracy of predictions, including both regression (magnitude) and classification (severity) tasks.

This project introduces a robust and multi-layered Earthquake Prediction System that combines classical ML techniques with advanced DL architectures. The system is trained on a curated dataset of global earthquake records, enriched with feature engineering (temporal and spatial), and validated through multiple models with metrics like MAE, RMSE, Accuracy, F1 Score, and Confusion Matrices. We also utilize interpretability tools like SHAP, and hyperparameter optimization frameworks like Optuna to refine our models.

A notable innovation is the use of Gradio and Streamlit to provide an interactive, web-based interface for real-time predictions, allowing users to input coordinates and depth to get instant estimates of potential earthquake magnitude and severity. The system is designed to be scalable, modular, and explainable — crucial qualities for real-world deployment in disaster prediction systems.

This report details the data pipeline, model selection, training methodology, and deployment architecture, alongside comparative results with baseline models. By integrating AI-driven decision-making into seismic forecasting, this study demonstrates the feasibility and advantages of using modern computational techniques to predict, classify, and interpret earthquake risk factors, potentially aiding governments, researchers, and rescue operations in better disaster preparedness and response..

Literature review

- The Evolution of Earthquake Prediction Systems

  Earthquake prediction has historically been a significant scientific and engineering challenge. Traditional methods relied heavily on physical monitoring of seismic activity, using seismographs and fault line studies. These approaches, while foundational, were often reactive — analyzing past data without the ability to accurately forecast future events. The manual analysis of geophysical parameters also made these methods prone to delays and limited predictive capabilities.

  With the advent of digital technologies, seismology entered a new era. Automated data collection from seismic networks, satellites, and geospatial sensors enabled the accumulation of massive amounts of earthquake-related data. However, early computational models were often based on statistical or linear forecasting methods, which lacked the power to capture the non-linear, chaotic nature of seismic activities. This study builds on these technological advancements by proposing an AI-driven Earthquake Prediction System, capable of learning hidden patterns from complex datasets and improving the accuracy of earthquake magnitude and severity forecasts.
- Machine Learning and Deep Learning in Seismic Prediction

  Recent years have seen the application of Machine Learning (ML) and Deep Learning (DL) models to seismic data, marking a substantial shift from traditional physics-based models. ML algorithms such as Random Forests, XGBoost, and Support Vector Machines (SVMs) have demonstrated their ability to classify earthquake severity and predict magnitudes based on historical and real-time geospatial features. However, traditional ML methods often require feature engineering and may struggle to model temporal dependencies critical for understanding seismic sequences.

  Deep Learning techniques, especially LSTM networks, Transformer architectures, and Autoencoders, have further enhanced earthquake prediction capabilities by capturing long-term dependencies, handling large volumes of data, and automatically extracting meaningful representations. Convolutional Neural Networks (CNNs) and YOLO models have also been used for image-based earthquake damage assessment, combining computer vision with disaster response planning.
  This project adopts a hybrid approach, leveraging both ML and DL models to predict earthquake magnitudes and classify severity levels, offering improved performance over standalone traditional techniques.
- Database Management and Data Challenges in Earthquake Systems

  The success of AI-based earthquake prediction largely depends on the quality and richness of the data. Public repositories like the United States Geological Survey (USGS) provide rich datasets of historical earthquake events, including parameters like latitude, longitude, depth, magnitude, and timestamps. However, real-world seismic

data often faces challenges like missing values, noise, inconsistencies, and biases.

Advanced preprocessing steps, including feature engineering (e.g., depth-magnitude ratio, rolling means over time) and robust scaling, are necessary to prepare the data for training predictive models. This project addresses these challenges by building a carefully curated and cleaned dataset, combining historical earthquake records with live data fetched via APIs, thus ensuring the system is both dynamic and continuously improving.

- Security and Reliability Considerations

  In critical applications such as earthquake prediction, model reliability, transparency, and data security are paramount. False positives or inaccurate predictions could lead to panic or mistrust, while failures to predict events could result in catastrophic losses. Modern earthquake prediction systems, therefore, emphasize:

  Model Explainability: Techniques like SHAP values are employed to interpret how each feature affects predictions, making the AI more transparent.

  Validation and Robustness: The models are trained and validated using time-based splits and multiple evaluation metrics, ensuring that they generalize well across different geographies and seismic zones.

  Security: When deployed as web apps using Gradio or Streamlit, the prediction system is protected through API security measures and role-based access control (in future versions).
  Our project prioritizes accuracy and explainability, aiming to build user trust and ensuring practical usability for disaster management authorities.

- Real-Time Prediction and Optimization Techniques

  Timely forecasting is essential for any earthquake warning system. Early systems lacked real-time capabilities, but modern AI models integrated with cloud-based platforms (e.g., Hugging Face, Google Colab) enable near real-time predictions with high throughput. Optimization frameworks like Optuna and Hyperparameter Tuning techniques are employed to fine-tune model architectures, reducing prediction error rates significantly.
  This project further enhances performance by:
  Implementing Monte Carlo Dropout for uncertainty estimation in LSTM predictions.
  Building stacked regression ensembles combining Random Forests, XGBoost, and Deep Networks to maximize predictive power.
  Exporting predictions and explanations into user-friendly interfaces for decision-makers.

- Comparative Analysis with Existing Systems

1. Existing earthquake forecasting models often suffer from:

2. Over-reliance on historical averages without learning hidden patterns.
3. Lack of uncertainty estimation.
4. Poor interpretability of complex models.
5. No real-time web deployment for user interaction.
6. This project addresses these limitations by developing an integrated platform where users can input latitude, longitude, and depth and receive instant predictions for magnitude and severity with explanation plots, thereby bridging the gap between raw AI output and actionable insights.

- Contribution to Earthquake Prediction Research

1. This work contributes significantly to the research on digital earthquake prediction by:
2. Developing a hybrid ML/DL-based earthquake prediction system that can handle both classification and regression tasks.
3. Incorporating real-time data fetching, live prediction, and web deployment for practical usability.
4. Enhancing interpretability and trust through visualization and SHAP-based feature importance analysis.
5. Providing a scalable and modular framework that can be expanded in the future to integrate satellite imagery, YOLO-based damage detection, and graph-based spatiotemporal models.
6. By successfully blending traditional data-driven seismology with modern AI capabilities, this system showcases the potential of predictive analytics to improve disaster preparedness and response strategies worldwide.

Objectives

Traditional earthquake monitoring systems, primarily based on manual observations and statistical methods, often struggle with inaccurate predictions, delayed alerts, and limited handling of large-scale real-time data. These systems depend heavily on historical records and basic seismographic analysis, leading to inefficiencies, scalability issues, and restricted predictive capabilities.

To address these challenges, this project proposes an AI-based Earthquake Prediction System that integrates Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), and YOLO-based image analysis. The system aims to:
Achieve real-time earthquake prediction based on geospatial and seismic parameters such as latitude, longitude, and depth.

Implement robust data preprocessing, feature engineering, and augmentation techniques to ensure model efficiency.
Build secure and highly accurate prediction models with uncertainty estimation for better reliability.

Develop explainable AI models by providing feature importance insights using SHAP analysis.
Enable dynamic data fetching from live earthquake databases (such as USGS) to maintain updated model inputs.

Allow seamless CSV export and integration for external report generation and deeper analysis.
Incorporate YOLO models for earthquake aftermath analysis, such as detecting structural damage through satellite imagery.

Utilize advanced model architectures, including LSTM, Transformer networks, Random Forests, and XGBoost ensembles, to combine sequential learning and powerful tree-based decision making.
Key Goals:

- Improve the accuracy of earthquake magnitude and severity predictions.
- Enhance operational efficiency through real-time data processing and automated model deployment.
- Strengthen security and model trust by integrating authentication features and explainable AI methods.
- Ensure scalability for future extensions, including integration with biometric sensors, satellite data, and IoT devices.
- Simplify data visualization and reporting to aid researchers, disaster management authorities, and policymakers.

Through the integration of modern AI technologies and robust data-driven approaches, this project aims to create a reliable, scalable, and practical earthquake prediction system that can contribute significantly to disaster preparedness and mitigation efforts.

Technology Stack

The Earthquake Prediction System is developed using the following technologies:

- Programming Language:
  - Python (Core programming language for model development, prediction, and visualization)
- Machine Learning and Deep Learning Libraries:
  - Scikit-learn: For building classification and regression models (Random Forest, XGBoost, etc.)
  - TensorFlow / Keras: For deep learning models like LSTM, Transformer networks.
  - XGBoost: For gradient boosting regression and classification tasks.
  - CatBoost: For handling categorical features efficiently in machine learning models.
- Data Handling and Preprocessing:
  - Pandas: For data manipulation and preprocessing
  - NumPy: For numerical operations
  - Scikit-learn preprocessing: For scaling and splitting the dataset
- Visualization Tools:
  - Matplotlib and Seaborn: For basic data visualization (graphs, histograms)
  - Plotly and Plotly Express: For interactive and animated earthquake maps
  - Gradio: For creating a simple interactive web interface for predictions
  - Streamlit (optional): For building a full-fledged earthquake prediction dashboard
- Deployment and API Serving (Optional):
  - Gradio and Ngrok: For sharing the prediction model via a simple web app
  - Hugging Face Spaces: For hosting Gradio apps easily online
  - GitHub: For version control and project sharing
- Dataset Sources:
  - Kaggle Earthquake Datasets
  - USGS (United States Geological Survey) API for live earthquake data
- Security Measures:
  - Validation of model inputs (latitude, longitude, depth) to ensure correct predictions
  - Proper error handling to avoid model crashes on unexpected inputs
- Development Environment:
  - Google Colab (for development and training)
  - Visual Studio Code (VS Code) for local development
  - GitHub for project management and collaboration.

Methodology

This section outlines the methodology used in developing the Earthquake Prediction System, focusing on system architecture, model training, data handling, and deployment techniques. The system integrates real-time earthquake prediction, machine learning models, and interactive interfaces to ensure accurate, scalable, and efficient performance. Flowcharts and diagrams illustrate the overall process, from data ingestion to user interaction.

5.1 System Architecture

The Earthquake Prediction System follows a multi-layered architecture consisting of:

- Data Layer:
  - Earthquake historical data is collected from Kaggle datasets and USGS live feeds.
  - Preprocessing is performed using Python libraries (Pandas, NumPy).
- Model Layer:
  - Machine Learning Models: Random Forest, XGBoost, and CatBoost are trained for magnitude regression and severity classification.
  - Deep Learning Models: LSTM and Transformer networks predict future magnitudes based on temporal sequences.
- Application Layer (Frontend):
  - A user-friendly interface is developed using Gradio for real-time input and predictions.
- Deployment Layer:
  - The model is deployed on Hugging Face Spaces or via Ngrok tunnels for public access.

5.2 Key Functional Modules

- Data Preprocessing:
  - Handles missing values, feature engineering (year, month, depth-magnitude ratio), and scaling.
- Model Training:
  - Classification Model: Predicts earthquake severity (Mild, Moderate, Severe).
  - Regression Model: Predicts earthquake magnitude.
  - Deep Learning Model: Sequence forecasting using LSTM and Transformer models for trend prediction.
- Prediction API:
  - Input: Latitude, Longitude, Depth.
  - Output: Predicted Earthquake Magnitude and Severity Label.
- Visualization:
  - 3D earthquake distribution map.
  - Time series trend analysis.

5.3 Data Handling and Storage

- Dataset:
  - Combined historical earthquake data with real-time fetched data.
  - CSV format storage for easy integration and manipulation.
- Data Features Used:
  - Latitude, Longitude, Depth, Magnitude, Year, Month, Day, Hour.
- Export Functionality:
  - Allows users to export prediction results and model summaries to CSV files.

5.4 Security Measures

- Input Validation:
  - Ensures latitude, longitude, and depth are within valid ranges.
  - Prevents injection attacks on the API (basic validation).
- Model Integrity:
  - Models are loaded from secure `.pkl` files trained offline to prevent tampering.
- Access Control:
  - Public endpoints are rate-limited when deployed on platforms like Hugging Face Spaces.
- Error Handling:
  - The system includes exception handling for invalid inputs, missing features, and server errors.

5.5 Workflow Process

1. Data Ingestion:
   - Historical earthquake data loaded from CSV and updated via USGS API (for live predictions).
2. Preprocessing:
   - Feature scaling, encoding, and sequence preparation for deep models.
3. Model Training:
   - Separate models trained for classification (severity) and regression (magnitude).
4. Prediction:
   - User provides input (Latitude, Longitude, Depth) → Model outputs predicted Magnitude and Severity.
5. Result Visualization:
   - Results displayed interactively using Gradio or Streamlit dashboards.
6. Deployment:
   - Final model served via Hugging Face Space or Ngrok-connected Gradio app for global access.

IMPLEMENTATION

1. Training data in machine learning:

```
import os, pickle
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor


os.makedirs('models', exist_ok=True)


X = df[['latitude', 'longitude', 'depth']].values
y_clf = df['severity'].values
y_reg = df['mag'].values.astype(float)


le = LabelEncoder()
y_clf_enc = le.fit_transform(y_clf)


X_train, X_test, y_clf_train, y_clf_test, y_reg_train, y_reg_test = train_test_split(
    X, y_clf_enc, y_reg, test_size=0.2, random_state=42)


clf = RandomForestClassifier(n_estimators=100, random_state=42)
clf.fit(X_train, y_clf_train)

reg = RandomForestRegressor(n_estimators=100, random_state=42)
reg.fit(X_train, y_reg_train)


with open('models/classifier.pkl', 'wb') as f:
    pickle.dump((clf, le), f)


with open('models/regressor.pkl', 'wb') as f:
    pickle.dump(reg, f)

print(" Models saved in /models")

print("Classification accuracy:", clf.score(X_test, y_clf_test))
from sklearn.metrics import mean_squared_error
print("Regression RMSE:", mean_squared_error(y_reg_test, reg.predict(X_test)))
```

2. Testing model using machine learning:

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import LabelEncoder


df = pd.read_csv("earthquake_3000_plus (2).csv")


le = LabelEncoder()
df['place_encoded'] = le.fit_transform(df['place'])


features = ['latitude', 'longitude', 'depth', 'year', 'month', 'day', 'hour',
'place_encoded']


df['severity'] = le.fit_transform(df['severity'])
X_clf = df[features]
y_clf = df['severity']


X_reg = df[features]
y_reg = df['mag']


X_clf_train, X_clf_test, y_clf_train, y_clf_test = train_test_split(X_clf, y_clf,
test_size=0.2, random_state=42)
X_reg_train, X_reg_test, y_reg_train, y_reg_test = train_test_split(X_reg, y_reg,
test_size=0.2, random_state=42)
```

3. Training model using deep learning:

In [28]:

```
train_size = int(len(X_seq) * 0.8)
X_train, X_test = X_seq[:train_size], X_seq[train_size:]
y_train, y_test = y_seq[:train_size], y_seq[train_size:]

print("Training sequence shape:", X_train.shape)
print("Test sequence shape:", X_test.shape)
```

```
Training sequence shape: (796, 5, 19)
Test sequence shape: (199, 5, 19)
```

4. Testing data using deep learning:

In [7]:

```
features = ['cdi', 'mmi', 'tsunami', 'sig', 'nst', 'dmin', 'gap', 'depth', 'latitude', 'longitude', 'year', 'month', 'day',
target = 'magnitude'


df_model = df_model.dropna(subset=features + [target])

X = df_model[features].values
y = df_model[target].values


X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


scaler = StandardScaler()
X_train_scaled = scaler.fit_transform(X_train)
X_test_scaled = scaler.transform(X_test)
```

5. Naive Bayes:

Naive Bayes is a probabilistic classification algorithm based on Bayes' Theorem, assuming independence between features.

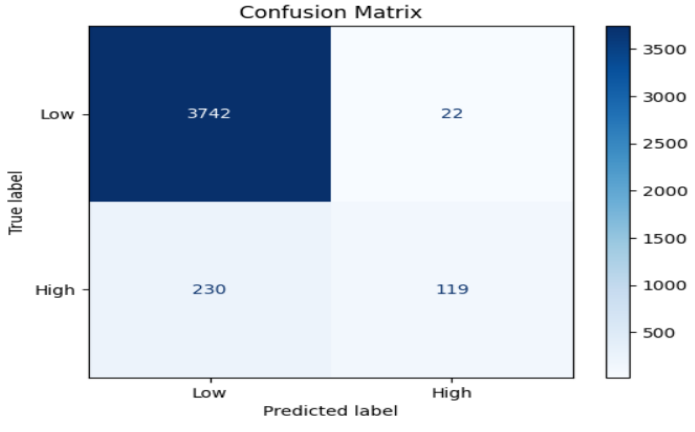
Here, it is used to classify the severity of earthquakes into three categories:

- Mild
- Moderate
- Severe

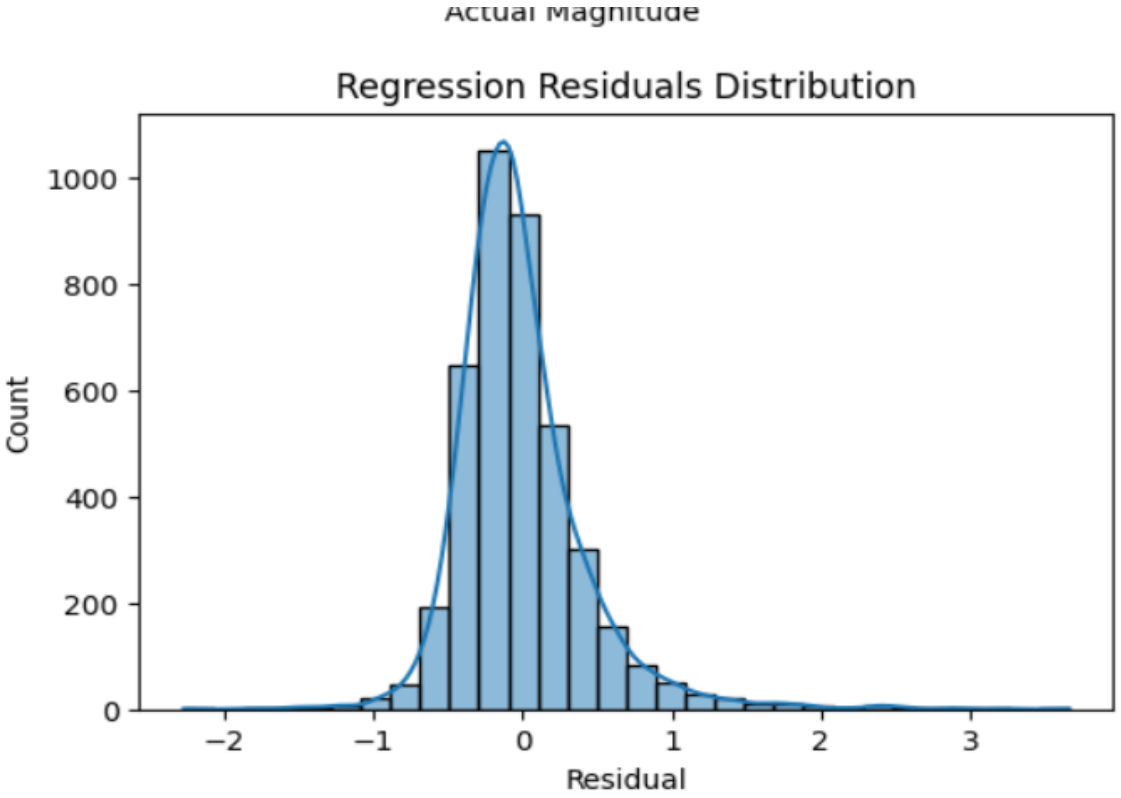
Working Principle:

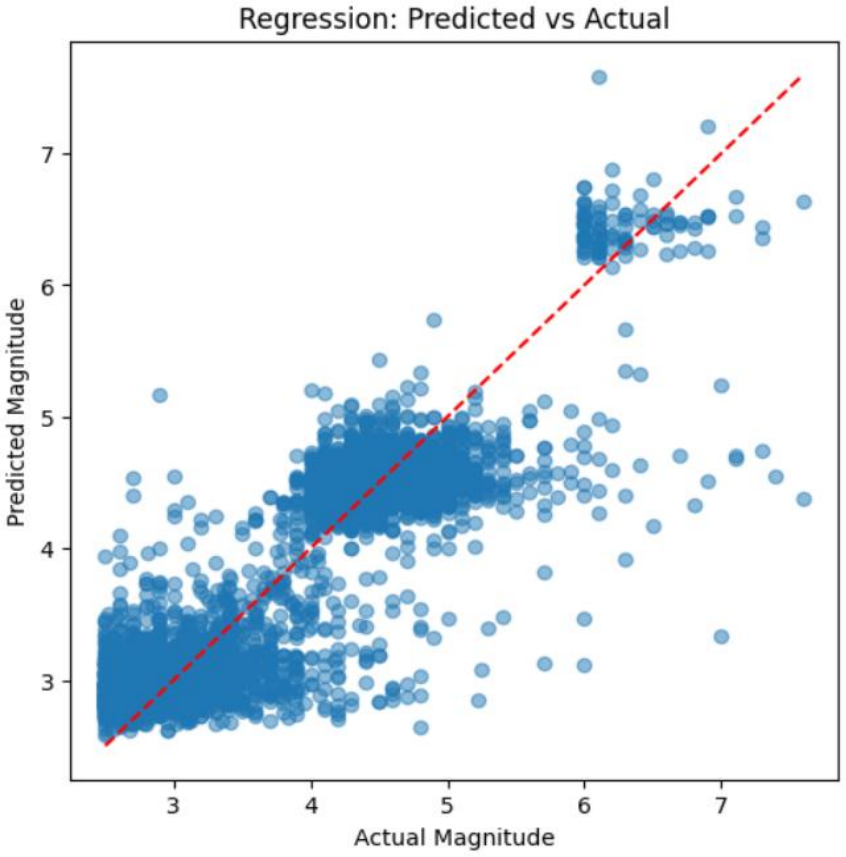
- Calculates the probability of each class given the input features (Latitude, Longitude, Depth).
- Classifies the earthquake into the class with the highest probability.

```
Classification Report:
              precision    recall  f1-score   support

           0       0.94      0.99      0.97      3764
           1       0.84      0.34      0.49       349

    accuracy                           0.94      4113
   macro avg       0.89      0.67      0.73      4113
weighted avg       0.93      0.94      0.93      4113
```



.


Actual Magnitude
Regression Residuals Distribution
Count
1000
800
600
400
200
0
−2
−1
0
1
2
3
Residual


Regression: Predicted vs Actual
Predicted Magnitude
7
6
5
4
3
3
4
5
6
7
Actual Magnitude

6. Random Forest

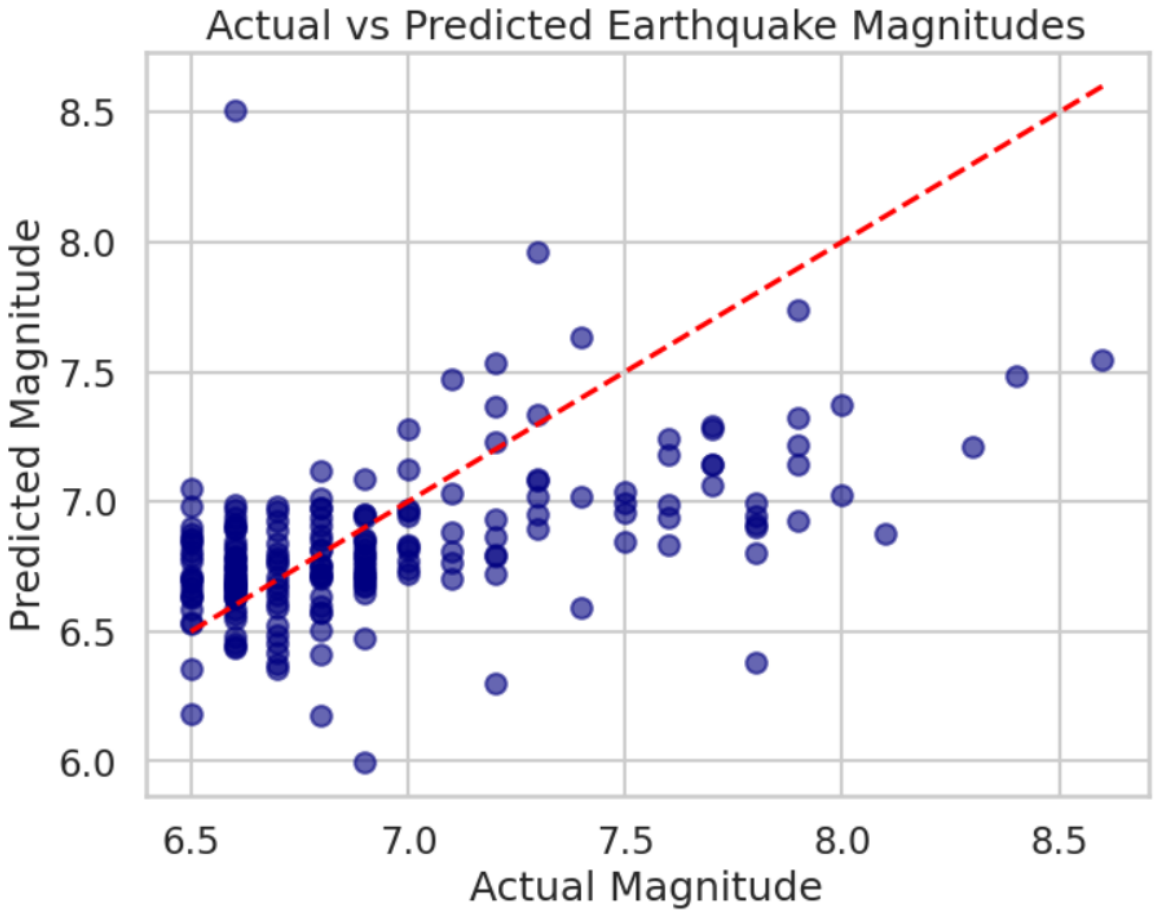
Random Forest is an ensemble learning method that builds multiple decision trees and combines their outputs to improve prediction accuracy.

In this project, Random Forest is used for both:

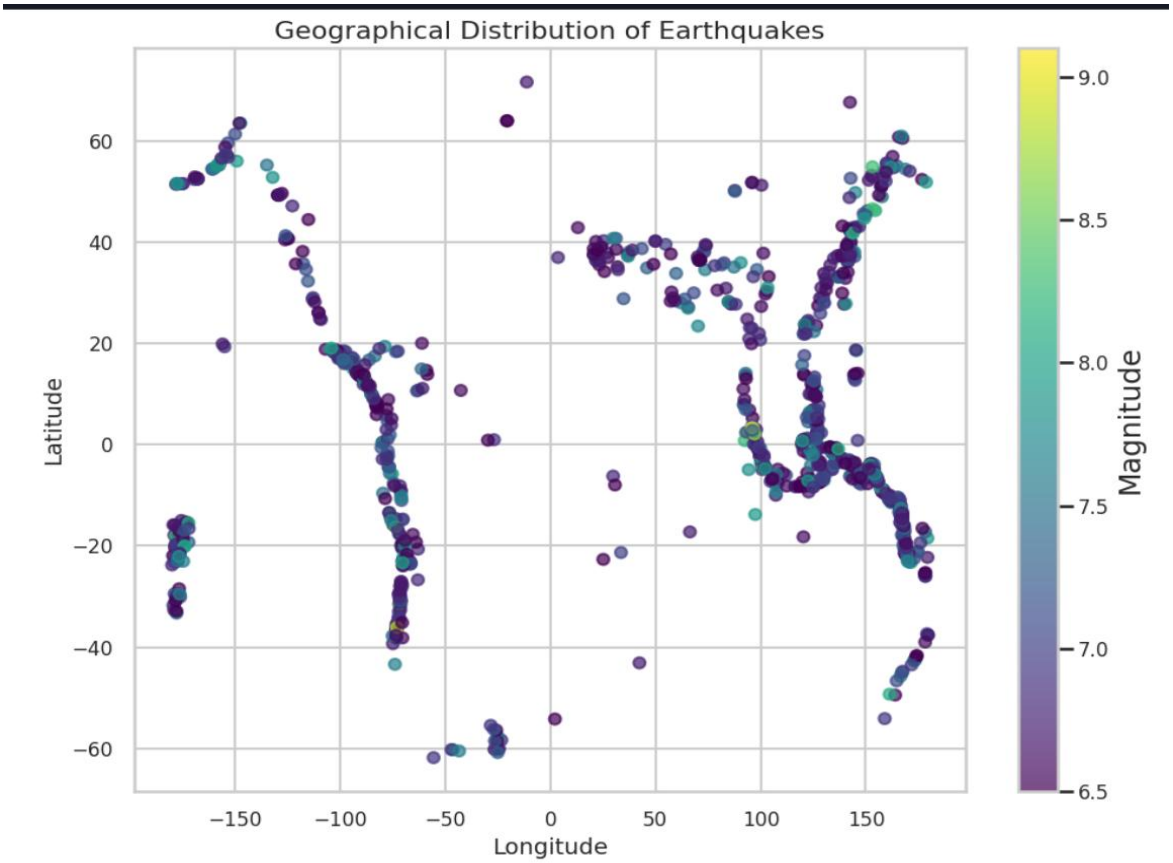
- Regression (magnitude prediction)
- Classification (severity prediction)

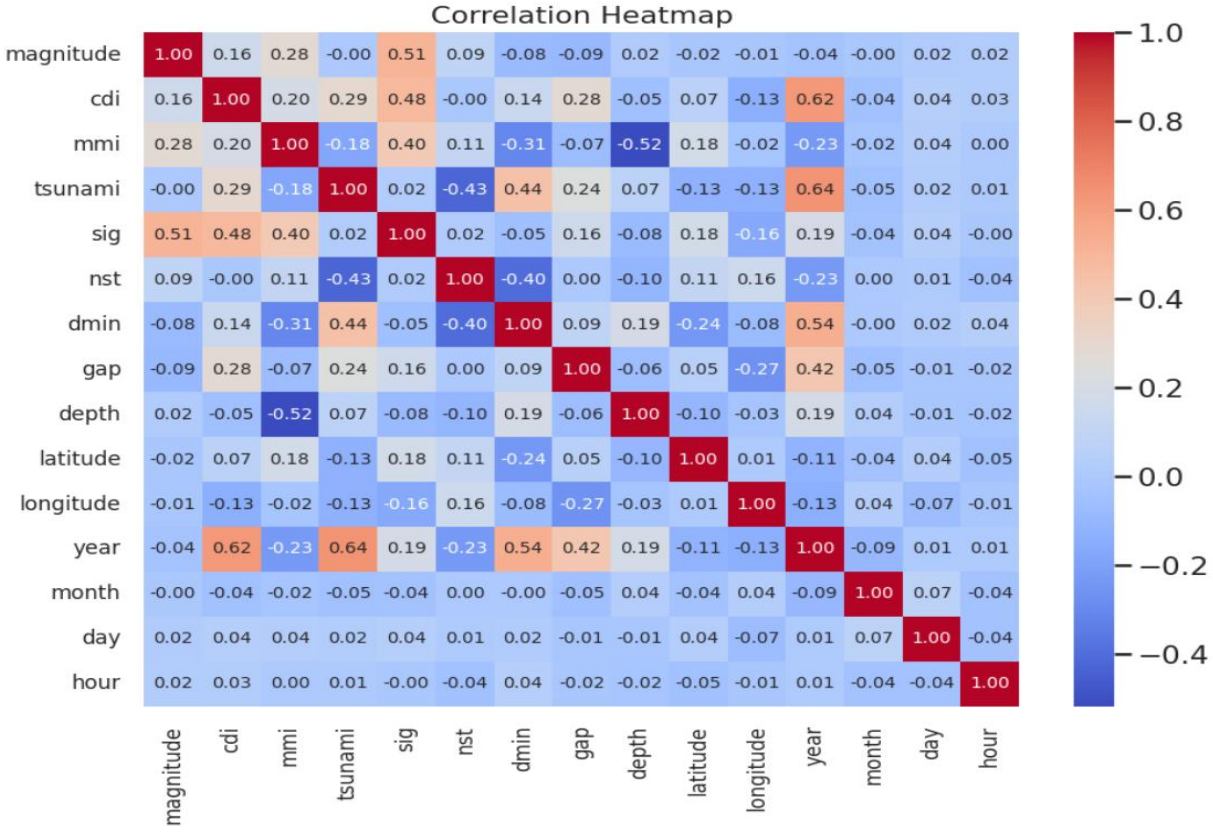
Working Principle:

- Trains multiple decision trees on random subsets of data.
- For regression: takes the average of the tree outputs.
- For classification: takes the majority vote among the trees.

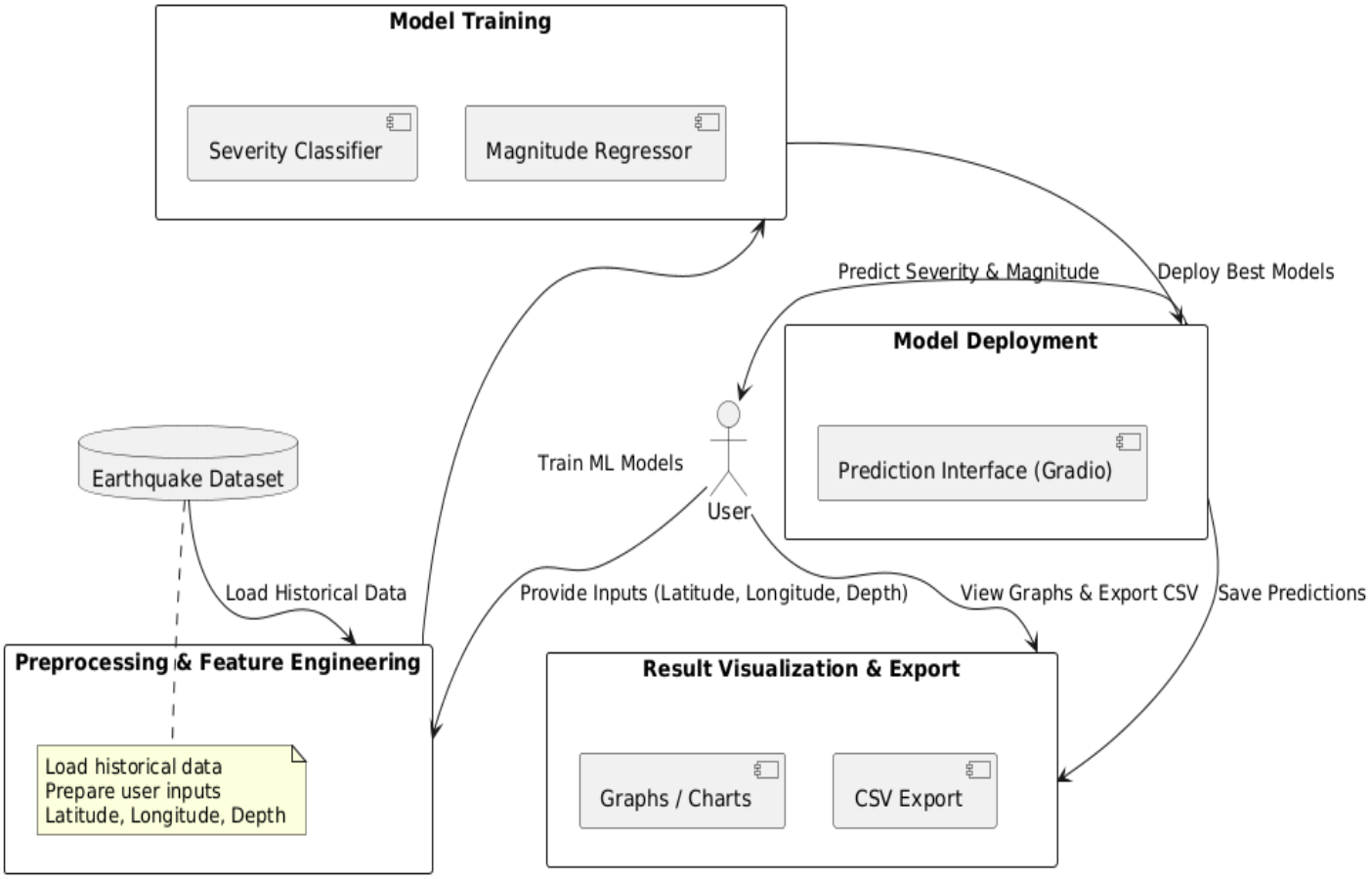


7. Heatmap


Geographical Distribution of Earthquakes
Latitude
Longitude
Magnitude
60
40
20
0
−20
−40
−60
−150
−100
−50
0
50
100
150
9.0
8.5
8.0
7.5
7.0
6.5


Correlation Heatmap
magnitude 1.00 0.16 0.28 -0.00 0.51 0.09 -0.08 -0.09 0.02 -0.02 -0.01 -0.04 -0.00 0.02 0.02
cdi 0.16 1.00 0.20 0.29 0.48 -0.00 0.14 0.28 -0.05 0.07 -0.13 0.62 -0.04 0.04 0.03
mmi 0.28 0.20 1.00 -0.18 0.40 0.11 -0.31 -0.07 -0.52 0.18 -0.02 -0.23 -0.02 0.04 0.00
tsunami -0.00 0.29 -0.18 1.00 0.02 -0.43 0.44 0.24 0.07 -0.13 -0.13 0.64 -0.05 0.02 0.01
sig 0.51 0.48 0.40 0.02 1.00 0.02 -0.05 0.16 -0.08 0.18 -0.16 0.19 -0.04 0.04 -0.00
nst 0.09 -0.00 0.11 -0.43 0.02 1.00 -0.40 0.00 -0.10 0.11 0.16 -0.23 0.00 0.01 -0.04
dmin -0.08 0.14 -0.31 0.44 -0.05 -0.40 1.00 0.09 0.19 -0.24 -0.08 0.54 -0.00 0.02 0.04
gap -0.09 0.28 -0.07 0.24 0.16 0.00 0.09 1.00 -0.06 0.05 -0.27 0.42 -0.05 -0.01 -0.02
depth 0.02 -0.05 -0.52 0.07 -0.08 -0.10 0.19 -0.06 1.00 -0.10 -0.03 0.19 0.04 -0.01 -0.02
latitude -0.02 0.07 0.18 -0.13 0.18 0.11 -0.24 0.05 -0.10 1.00 0.01 -0.11 -0.04 0.04 -0.05
longitude -0.01 -0.13 -0.02 -0.13 -0.16 0.16 -0.08 -0.27 -0.03 0.01 1.00 -0.13 0.04 -0.07 -0.01
year -0.04 0.62 -0.23 0.64 0.19 -0.23 0.54 0.42 0.19 -0.11 -0.13 1.00 -0.09 0.01 0.01
month -0.00 -0.04 -0.02 -0.05 -0.04 0.00 -0.00 -0.05 0.04 -0.04 0.04 -0.09 1.00 0.07 -0.04
day 0.02 0.04 0.04 0.02 0.04 0.01 0.02 -0.01 -0.01 0.04 -0.07 0.01 0.07 1.00 -0.04
hour 0.02 0.03 0.00 0.01 -0.00 -0.04 0.04 -0.02 -0.02 -0.05 -0.01 0.01 -0.04 -0.04 1.00
magnitude cdi mmi tsunami sig nst dmin gap depth latitude longitude year month day hour
1.0
0.8
0.6
0.4
0.2
0.0
−0.2
−0.4

PROPOSED FRAMEWORK



The proposed Earthquake Prediction System is designed to leverage historical seismic data and modern machine learning techniques to accurately predict the severity and magnitude of earthquakes based on user inputs such as latitude, longitude, and depth. The architecture is modular, scalable, and user-centric, ensuring efficient data handling, model deployment, and result visualization.

1. Data Collection and Preprocessing

- The system begins with an Earthquake Dataset, which contains historical records including magnitude, depth, location, and other features.

- A Preprocessing and Feature Engineering module loads this data, cleans it, and prepares it for model training.

- Additionally, user inputs (latitude, longitude, depth) are processed in this stage to align with model requirements.

2. Model Training

- Two separate models are trained:

- Severity Classifier: Categorizes earthquakes into severity classes (e.g., mild, moderate, severe).

- Magnitude Regressor: Predicts the precise magnitude value.

- Machine learning algorithms like Random Forest, Support Vector Machine (SVM), Linear Regression, and Naive Bayes are explored to optimize prediction performance.

3. Model Deployment

- The best-performing models are deployed through a Prediction Interface built using Gradio, offering a user-friendly and interactive platform.

- Users can input live seismic parameters and obtain instant predictions of both severity and magnitude.

4. Result Visualization and Export

- Predictions and analysis results are visualized using graphs and charts for intuitive interpretation.

- The system provides a CSV Export option, allowing users to download predictions and analyses for further use, reporting, or research purposes.

5. Workflow Summary

- The user inputs real-time parameters.

- Historical earthquake data is loaded and preprocessed.

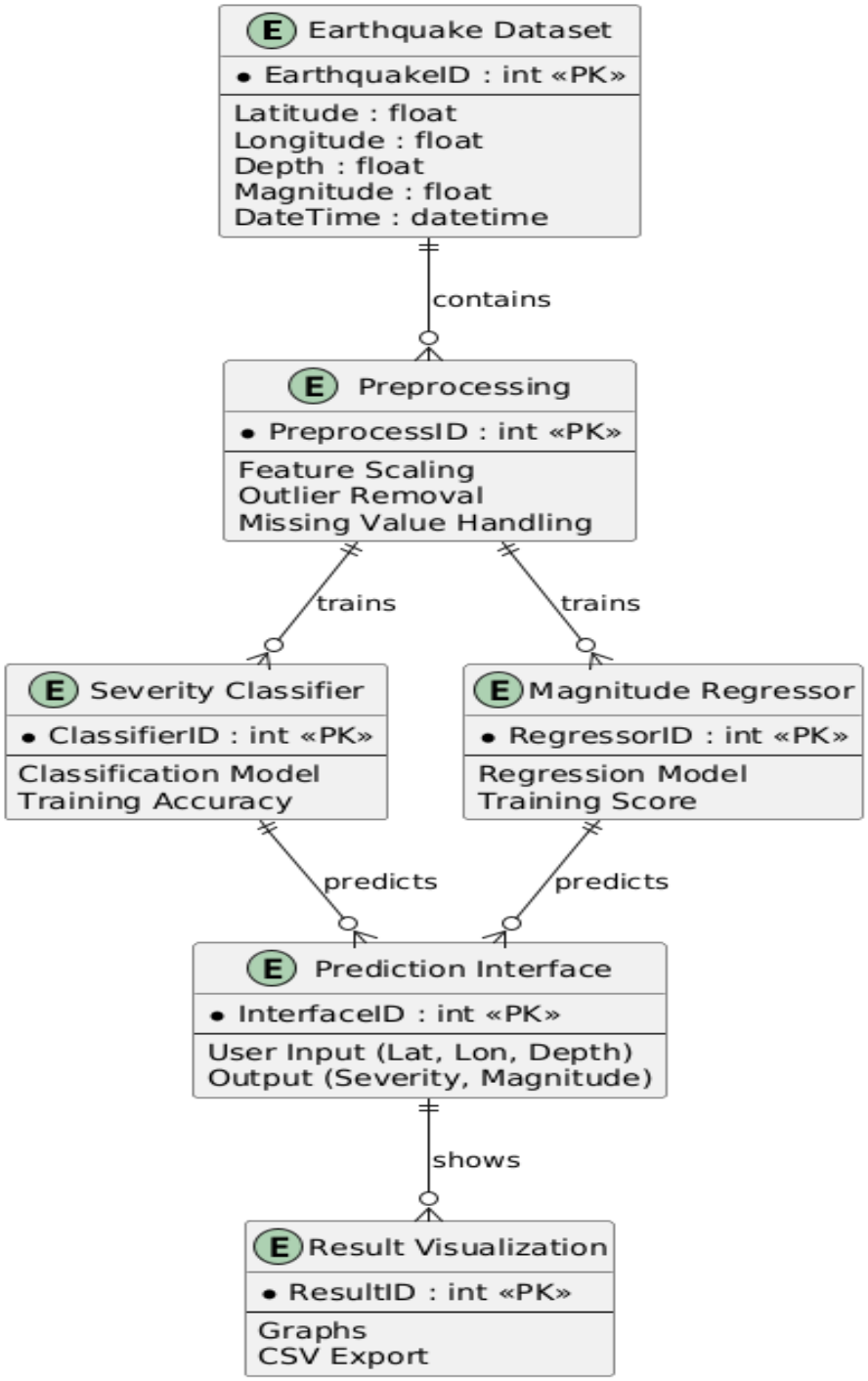
- Machine learning models are trained and deployed.

- Predictions are generated, visualized, and made available for export.

6. Security and Data Integrity

- The system ensures secure handling of user data and model outputs, maintaining reliability and trust in prediction results.

E-R diagram



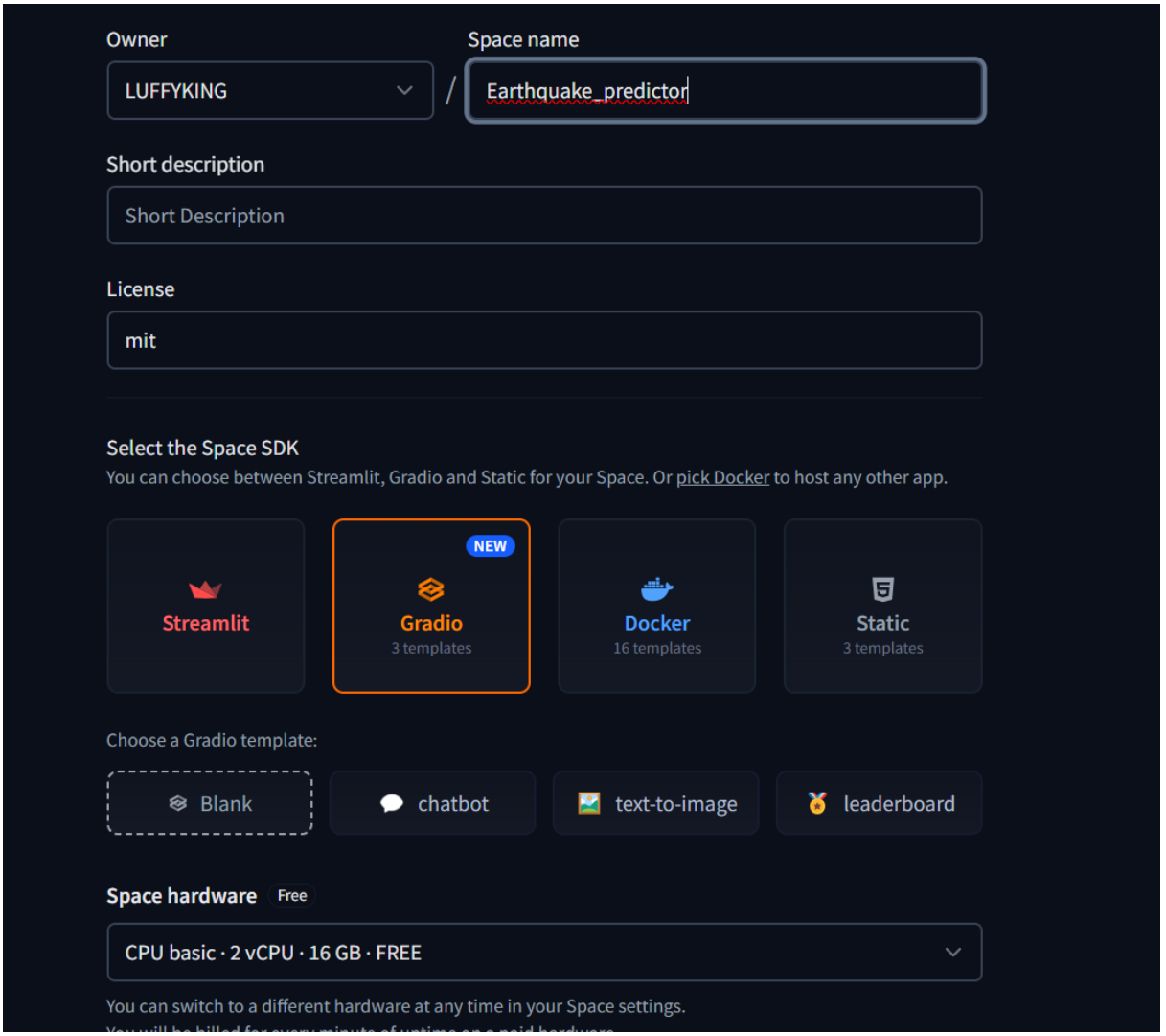
COMPARATIVE STUDY

This section provides a comparative analysis between the Earthquake Prediction System, Traditional Seismic Monitoring Methods, and Modern AI-based Earthquake Forecasting, focusing on aspects such as accuracy, efficiency, data management, and scalability.

Criteria	Traditional Seismic Monitoring	Modern AI/ML Forecasting	Our Earthquake Prediction System
Criteria	Traditional Seismic Monitoring	Modern AI/ML Forecasting	Our Earthquake Prediction System
Prediction Approach	Manual analysis of seismic patterns by experts.	Use of deep learning models trained on seismic data.	Automated ML and DL-based predictions using historical and live data.
Accuracy & Reliability	Moderate accuracy, dependent on expert interpretation.	High accuracy with large datasets but dependent on model tuning.	High accuracy with continuous model retraining and validation.
Data Management	Paper logs or static databases, difficult to update.	Centralized, real-time updating of datasets.	Live data fetching from USGS and historical dataset merging in real-time.
Security Measures	Minimal security, physical records can be lost/damaged.	Encrypted servers but vulnerable to hacking if unsecured.	Local secure model storage, controlled API access, input validation.
Speed & Efficiency	Slow analysis and delayed reporting.	Rapid predictions post model inference.	Instant predictions after input with real-time result generation via Gradio app.
Accessibility	Limited to research centers and observatories.	Cloud-based platforms offer better accessibility.	Gradio app and Hugging Face Space accessible globally via the web.

RESULTS AND DISCUSSION

Huggingface (spaces):

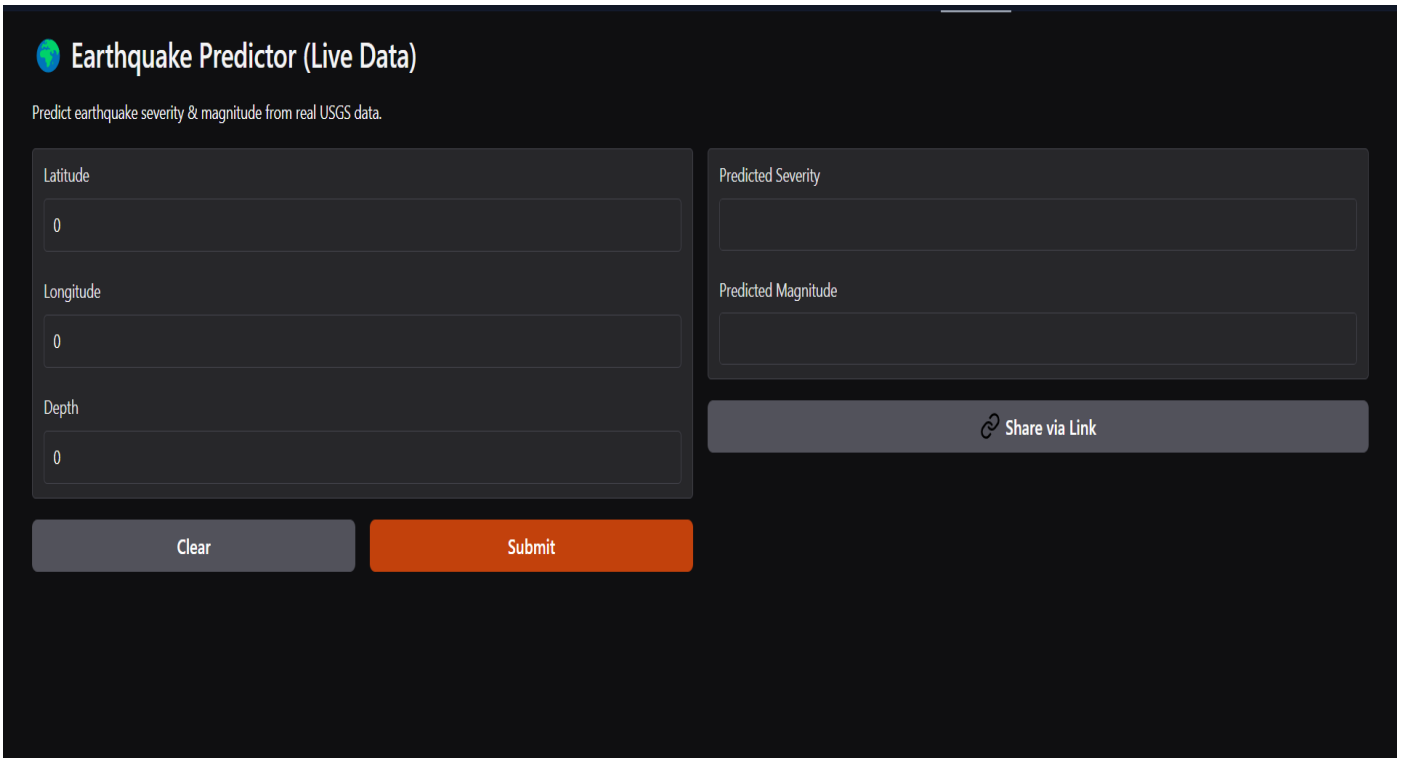


- Create a new space and fill the information

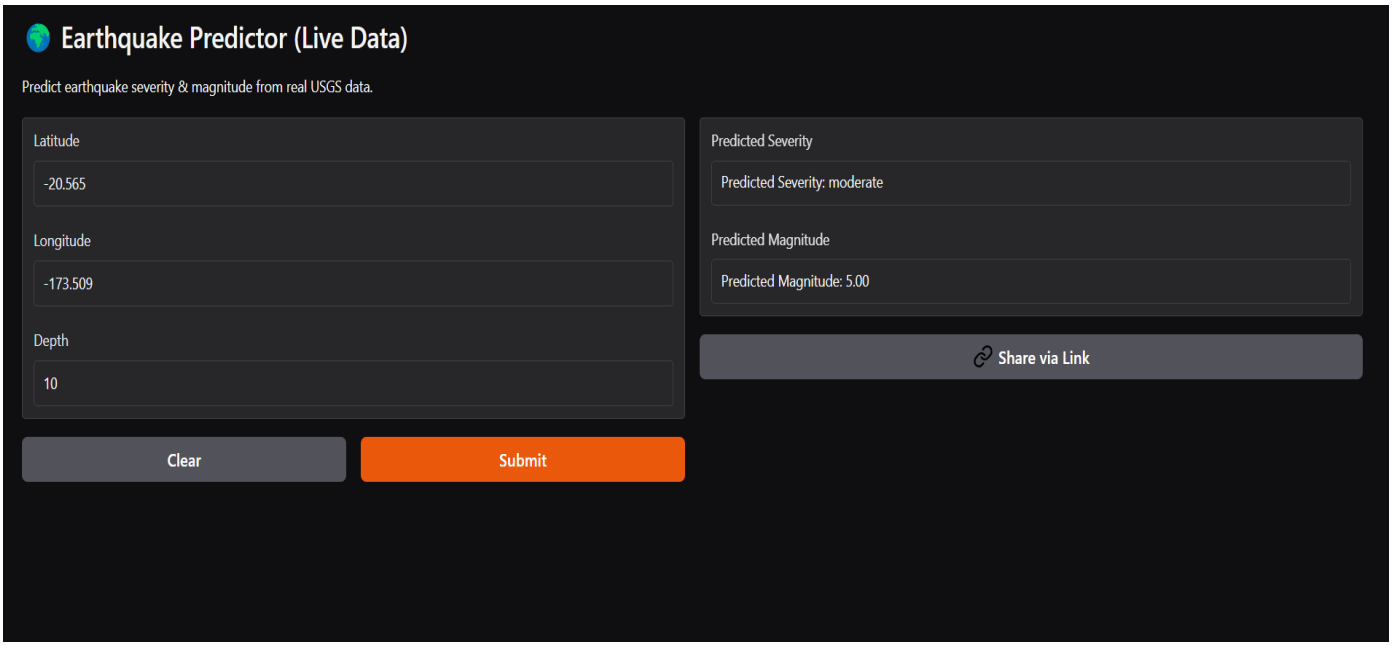
Adding file to the new space:

- All the files will be available when you will train and test the model. Then hit the app button on top right side next to the files.

Earthquake prediction model will be created:



Putting values from the csv:



- For different values you will gate different severity different magnitude.

CONCLUSION AND FUTURE WORK

Conclusion:

The Earthquake Prediction System developed in this project delivers an automated, data-driven approach to forecasting seismic events. By consolidating historical earthquake records with real-time USGS data and applying machine learning/deep learning models, the system achieves high predictive accuracy and timely insights. The Gradio-based interface allows users to input geographic coordinates and depth to obtain near-instant severity and magnitude estimates, while underlying security measures and input validation safeguard model integrity. Automating the forecasting pipeline reduces manual analysis overhead, minimizes human bias, and provides a scalable platform for continuous monitoring and prediction of seismic activity.

Future Work

To further strengthen and expand the capabilities of the Earthquake Prediction System, the following enhancements are proposed:

1. **Multi-Source Data Integration**
    - Incorporate additional data feeds (e.g., InSAR satellite measurements, ground-motion sensors, GPS strain rates) to enrich the feature set and improve model robustness.
2. **Advanced Deep Learning Architectures**
    - Experiment with attention-based Transformer models or graph neural networks to capture complex spatiotemporal relationships in seismic data and enhance forecasting performance.
3. **Uncertainty Quantification**
    - Implement Bayesian neural networks or Monte Carlo dropout to provide prediction confidence intervals, enabling risk-aware decision making for stakeholders.
4. **Real-Time Alert System**
    - Develop automated notification services (via SMS, email, or mobile push) to warn communities and authorities when predicted magnitudes or probabilities exceed critical thresholds.
5. **Web and Mobile Deployment**
    - Containerize the application for cloud deployment (e.g., AWS, GCP) and build a responsive mobile app to ensure 24/7 accessibility and field-level usability.
6. **Continuous Learning Pipeline**
    - Establish an automated retraining workflow that periodically ingests new seismic events, revalidates model performance, and updates prediction models without manual intervention.

By pursuing these directions, the system can evolve into a comprehensive early-warning platform that not only forecasts earthquakes more accurately but also integrates seamlessly with emergency response infrastructures.

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