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Online Examination System with Timer & Leaderboard

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ABSTRACT

The AI for Earthquake Damage prediction system is a web-based platform that predicts earthquake damage severity using machine learning. It analyses parameters like magnitude, depth, epicentre, soil type, and building details for accurate predictions. The system integrates real-time seismic and geospatial data to support rapid disaster response. Developed using Python and Flask, it offers a simple, user- friendly interface. The model improves resource allocation and emergency planning. It helps authorities and rescue teams make quick, data-driven decisions. Automated predictions and rescue teams make quick, data-driven decisions.

KEYWORDS

Earthquake Prediction; Artificial Intelligence; Machine Learning; Data Preprocessing; Magnitude and Depth Estimation; Damage Assessment; Flask Web Application.

INTRODUCTION

Among the most devastating natural disasters, earthquakes have the potential to cause significant economic harm, a significant loss of human life, and long- term social unrest. Numerous catastrophic earthquakes throughout history have brought attention to the pressing need for precise forecasting and readiness. Conventional seismic monitoring systems mainly concentrate on real-time event detection and early warning, even though they are successful in identifying earthquake events and sending out alerts. They frequently fall short, though, in offering more profound understandings of the probable extent, depth, and damage assessment all of which are essential for disaster management and resource distribution. With the rapid development of Artificial Intelligence (AI) and Machine Learning (ML), there has been a significant shift toward data-driven approaches for predictive modelling in seismology. AI techniques enable the analysis of vast amounts of historical earthquake data.

LITERATURE REVIEW

The application of machine learning (ML) and artificial intelligence (AI) techniques has led to a considerable evolution in the field of earthquake damage prediction. Conventional approaches mostly depended on statistical and seismological models, which frequently lacked accuracy and flexibility in practical situations. Recent research has shown that data-driven methods may efficiently evaluate environmental, structural, and seismic factors to forecast possible damage. When researchers like Li et al. (2020) used convolutional neural networks (CNNs), a type of deep learning, to analyse spatial seismic data, they were able to enhance prediction accuracy over regression models. In a similar vein, Maqsood et al. (2019) reported greater classification precision when they used a Random Forest classifier to assess building damage during the Nepal earthquake.

RELATED WORK

Several researchers have explored the use of Artificial Intelligence (AI) and Machine Learning (ML) techniques for earthquake damage prediction and assessment. Li et al. (2020) implemented deep learning models such as Convolutional Neural Networks (CNNs) to analyse seismic data and predict earthquake intensity with high accuracy. Maqsood et al. (2019) used a Random Forest classifier to evaluate building damage after the Nepal earthquake, demonstrating improved results compared to traditional regression models. Dixit et al. (2022) proposed a hybrid model combining Gradient Boosting Machines (GBM) and Support Vector Machines (SVM) for accurate damage probability estimation. Islam et al. (2021) integrated neural networks with Geographic Information Systems (GIS) to generate spatial damage maps for real-time disaster management.

EXISTING METHOD

Existing earthquake damage prediction methods mainly depend on traditional seismic analysis and statistical models that estimate damage based on fixed parameters such as magnitude, depth, and distance from the epicentre. Systems like USGS ShakeMap and national monitoring centres provide real-time earthquake detection and intensity maps; however, they often fail to accurately reflect the true extent of structural damage. These methods do not consider critical factors such as building design, soil type, material strength, and local terrain variations, which significantly influence damage severity. Moreover, most existing systems rely heavily on manual surveys and historical averages, making them slow, less adaptable, and prone to human error. The lack of integration between real-time seismic data, satellite imagery, and structural information limits their accuracy and usefulness during emergencies.

PROPOSED METHOD

The proposed system uses a machine learning-based approach integrated with a Flask web application to predict earthquake magnitude and depth. The user provides inputs such as date, time, latitude, and longitude, which are pre-processed and fed into the trained model. The model analyses historical earthquake patterns and geographical data to generate accurate predictions of the earthquake's magnitude and depth. Based on these values, the system also provides a damage prediction and depth analysis to estimate the possible surface impact. The Flask framework connects the prediction model with a user- friendly web interface, allowing real-time interaction and visualization of results. This approach enables users to easily understand potential earthquake effects and promotes awareness of seismic risks.

SYSTEM ARCHITECTURE

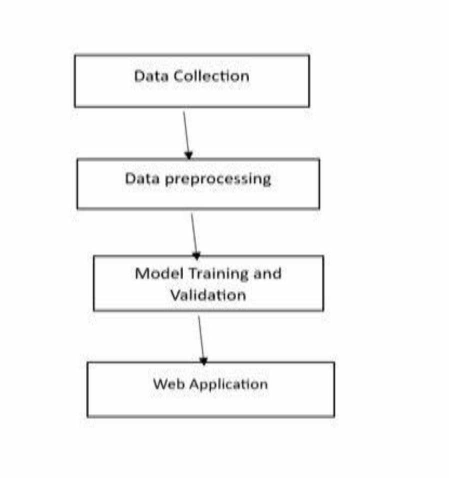

Fig1: Block Diagram

METHODOLOGY

Data Collection: Gather historical earthquake data containing date, time, latitude, longitude, depth, and magnitude from sources like USGS or Kaggle.

Data Preprocessing: Clean the dataset by handling missing values, extracting time features, and scaling data for better model performance.

Model Training and Validation: Train a machine learning model (e.g., Random Forest or XGBoost) on the processed data and evaluate it using metrics like MAE and RMSE.

Web Application: Integrate the trained model into a Flask web app to accept user input, run predictions, and display the magnitude, depth, and damage analysis results.

RESULTS AND DISCUSSION

Fig.2: Deploying the Model via Flask

Flask enables seamless integration of the machine learning model into a web-based application, allowing users to input earthquake parameters through a user- friendly interface and receive real-time damage predictions.

Fig.3: Web Interface for Earthquake Magnitude and Depth Prediction

the model's ability to differentiate damage levels based on multiple factors demonstrates its effectiveness in handling non-linear relationships inherent in earthquake damage prediction.

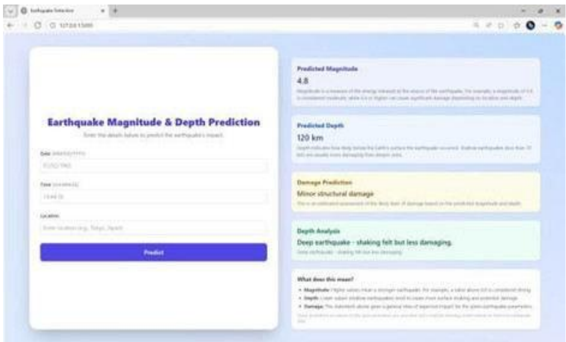

Fig.4: Web Interface for Earthquake Magnitude and Depth Prediction

These predictions align with real-world expectations higher magnitude, shallow depth, and older buildings tend to cause more damage. These results reinforce the model's ability to capture the complex interplay between seismic intensity, geological conditions, and structural vulnerability.

CONCLUSION

This project presents a Flask-based web application for predicting earthquake magnitude and depth using a machine learning model trained on historical data. It enables users to input basic parameters like date, time, latitude, and longitude to obtain real-time predictions. The system bridges data science and web technology, offering a simple yet effective way to analyse seismic activity. The result analysis shows that the trained model achieves satisfactory accuracy in predicting magnitude and depth within an acceptable error range. The web interface efficiently displays predictions

along with damage and depth analysis, enhancing user understanding of earthquake risks.

FUTURE SCOPE

In the future, this system can be enhanced by integrating deep learning models such as LSTM or CNN to capture complex seismic patterns for better accuracy. Additionally, geospatial visualization tools like Leaflet or Mapbox can be added to display earthquake locations on interactive maps of the concept. Implementing cloud deployment with automated data updates and alert systems can further upgrade the model into a real- time earthquake awareness platform.

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