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AI-POWERED EARTHQUAKE RESILIENCE: PREDICTIVE MODELING AND DAMAGE LEVEL ASSESSMENT FOR SEISMIC-RESISTANT STRUCTURES

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Abstract

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Assessing the seismic resilience of structures is critical for ensuring safety and minimizing economic losses during earthquakes. Traditional analysis methods, while detailed, often require significant computational resources and expertise, limiting their applicability for rapid evaluations or large-scale assessments. This study explores the potential of machine learning (ML) as an efficient alternative for predicting key seismic performance parameters. We developed predictive models using a dataset comprising building characteristics and seismic load information, including features such as Seismic Zone Classification, Peak Ground Acceleration (PGA), Building Height, Structural Type, Damper Type, Number of Storeys, Damping Ratio, and Soil Type. Random Forest algorithms were employed to build the predictive models: two Random Forest Regressors were trained to estimate Maximum Lateral Displacement (mm) and Base Shear Force (kN), and a Random Forest Classifier was trained to determine the Performance Level Classification (e.g., Immediate Occupancy, Life Safety, Collapse Prevention). Data preprocessing involved Label Encoding for categorical features and Standard Scaling for numerical features to prepare the data for model training. The models were trained and evaluated using a standard train-test split methodology. The results demonstrated the high predictive capability of the Random Forest approach for this problem. The regression models achieved excellent performance on the test set, with R-squared values exceeding 0.97 for both Maximum Lateral Displacement and Base Shear Force predictions, indicating a strong correlation between predicted and actual values. The Performance Level Classification model exhibited near-perfect accuracy (1.0 on the test set) and correspondingly high precision, recall, and F1-scores across all performance classes. To enhance accessibility and practical application, the trained models and preprocessing steps were integrated into a user-friendly web application developed using the Flask framework. This tool allows users to obtain rapid seismic performance predictions through either manual input of building/seismic parameters or batch processing via CSV file upload. This research highlights the efficacy of Random Forest algorithms for earthquake resilience prediction and provides a valuable tool for preliminary seismic assessment, potentially aiding engineers and stakeholders in design and decision-making processes.

Keywords: Seismic Performance, Structural Resilience, Machine Learning, Random Forest, Regression, Classification, Predictive Modeling, Data-Driven Analysis, Peak Ground Acceleration, Lateral Displacement, Base Shear, Performance Level Classification, Seismic Hazard Assessment.

1. INTRODUCTION

Earthquakes represent one of the most destructive natural hazards, capable of causing catastrophic damage to infrastructure, leading to significant economic losses and, most tragically, loss of life. The ability of buildings and other structures to withstand seismic events without collapse, ensuring the safety of occupants and maintaining functionality, is paramount. Therefore, accurately assessing the seismic performance and resilience of structures is a cornerstone of earthquake engineering, informing design practices, retrofitting strategies, and urban planning efforts aimed at mitigating seismic risk.

Traditionally, evaluating the seismic response of buildings involves complex and computationally intensive numerical simulations, such as non-linear time-history analysis or finite element modeling. While these methods provide detailed insights, they often demand substantial computational resources, significant time investment, and specialized expertise. This can limit their practicality for rapid vulnerability assessments, preliminary design evaluations, or large-scale screening of building inventories, creating a need for more efficient yet reliable prediction tools.

In recent years, the advent of machine learning (ML) and data-driven techniques has opened new avenues for tackling complex engineering problems. By learning patterns and relationships directly from data generated through simulations or experiments, ML models offer the potential to provide rapid and reasonably accurate predictions of structural behaviour under various conditions. This data-driven approach can serve as a valuable complement to traditional methods, particularly in scenarios requiring quick decision-making or the analysis of numerous structures.

Earthquakes are among the most devastating natural disasters, capable of causing severe structural damage, economic losses, and human casualties. The seismic resilience of buildings plays a crucial role in safeguarding communities and ensuring continuity of services during and after such events. Traditionally, the assessment of a structure's seismic performance relies on advanced analytical methods such as finite element modeling, pushover analysis, and non-linear time-history simulations. While these techniques provide in-depth insights into structural behavior under dynamic loads, they are resource-intensive, require detailed modeling expertise, and are often impractical for rapid assessments or large-scale building inventories. As urbanization intensifies and the need for timely disaster preparedness grows, there is a pressing demand for faster, scalable, and more accessible approaches to predict seismic response indicators like lateral displacement, base shear, and performance levels.

Recent advancements in machine learning (ML) have opened new avenues for structural engineering, allowing models to learn complex patterns from historical or simulated data and deliver accurate predictions with minimal computational overhead. Among the array of ML algorithms, Random Forest stands out for its robustness, versatility, and ability to handle both regression and classification tasks effectively. Leveraging these strengths, this study investigates the application of Random Forest models to predict earthquake-induced Maximum Lateral Displacement and Base Shear Force, along with Performance Level Classification (Immediate Occupancy, Life Safety, Collapse Prevention), based on essential building and seismic features. The chosen input features—such as Seismic Zone Classification, Peak Ground Acceleration (PGA), Building Height, Structural Type, Damper Type, Number of Storeys, Damping Ratio, and Soil Type—represent critical factors influencing a building's seismic behavior.

To translate these models into practical tools, a web-based application using the Flask framework is also developed, enabling users to input data manually or through CSV uploads to obtain instant predictions. This integration of machine learning with structural engineering not only facilitates rapid seismic assessments but also empowers engineers, planners, and decision-makers with a reliable, data-driven approach for enhancing earthquake resilience and informed design strategies. This research aims to bridge the gap between accuracy and efficiency in seismic assessment, providing a valuable contribution to modern earthquake engineering practices.

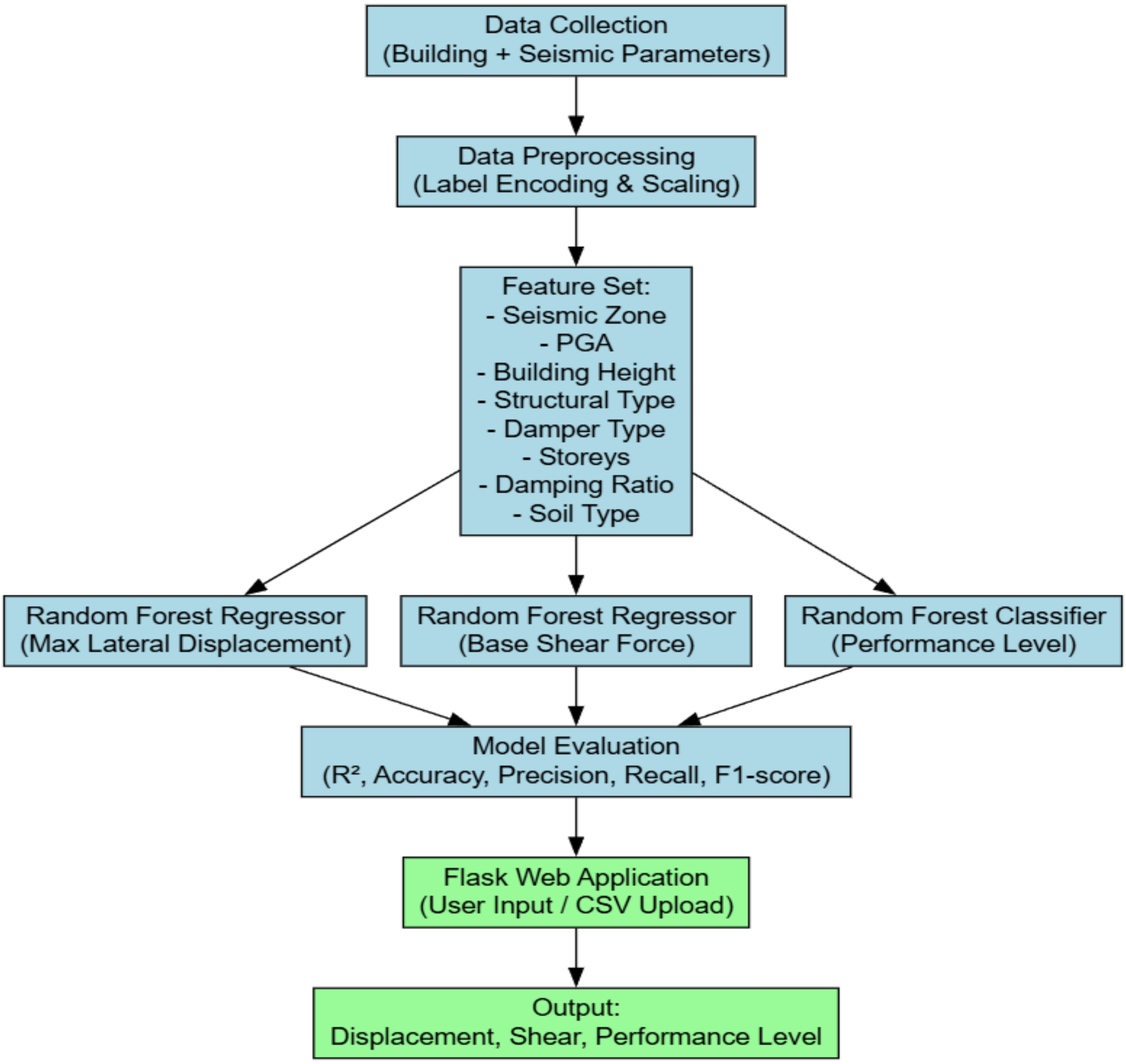


Fig 1 Workflow of Random Forest-Based Seismic Performance Prediction System

The remainder of this paper is organized as follows: Section 2 provides a review of relevant literature in seismic assessment and machine learning applications. Section 3 details the methodology, including the data preprocessing steps, the Random Forest algorithms, and the evaluation metrics used. Section 4 describes the dataset employed in this study. Section 5 presents and discusses the performance results of the trained models. Finally, Section 6 concludes the paper, summarizing the key findings and suggesting directions for future work.

2. PROBLEM STATEMENT

While essential for detailed seismic safety verification, conventional methods for assessing building performance under earthquake loads, such as non-linear time-history analysis and finite element modeling, present significant practical challenges. These approaches are inherently complex, computationally expensive, and time-consuming, often requiring detailed structural models and considerable engineering expertise to execute and interpret accurately. Consequently, their application becomes impractical for scenarios demanding rapid evaluations, including the preliminary stages of structural design, the seismic vulnerability assessment of large building inventories for urban planning or risk management, or rapid post-event screening. This creates a critical need for alternative, efficient predictive methodologies that can quickly provide reliable estimates of key seismic response indicators—namely maximum lateral displacement, base shear force, and overall performance level—without the prohibitive resource requirements associated with traditional detailed analysis techniques.

3. MOTIVATION

Earthquakes continue to pose a significant threat to build environments worldwide, especially in regions with high seismic activity. The safety and functionality of structures during and after an earthquake directly impact not only human life but also economic stability and recovery. Traditional seismic analysis techniques, such as finite element modeling and time-history analysis, though rigorous and reliable, are often computationally intensive and time-consuming. These methods require detailed structural information, high levels of expertise, and significant resources, making them less feasible for rapid assessment or large-scale screening of buildings in vulnerable urban areas.

With the increasing availability of structural and seismic data, there is a growing opportunity to apply machine learning approaches that can learn complex patterns from such data and deliver fast, accurate predictions of structural response. Among various machine learning methods, Random Forest stands out for its robustness, interpretability, and ability to handle both regression and classification tasks effectively. This motivates the exploration of Random Forest models to predict critical seismic performance parameters, such as lateral displacement, base shear, and performance level classifications, using easily measurable input features.

The motivation behind this research is to bridge the gap between high-fidelity simulation techniques and the urgent need for quick, scalable seismic performance assessments. By harnessing the power of data-driven modeling and integrating it into a user-friendly web application, this work aims to support engineers, urban planners, and decision-makers in performing timely and informed assessments of building resilience in the face of seismic hazards.

4. OBJECTIVES

1. Develop a Random Forest Regression model to predict Maximum Lateral Displacement (mm).
2. Develop a Random Forest Regression model to predict Base Shear Force (kN).
3. Create a Random Forest Classification model to categorize buildings into Performance Levels (IO, LS, CP).
4. Use key input features such as Seismic Zone, PGA, Building Height, Structural Type, Damper Type, Storeys, Damping Ratio, and Soil Type.
5. Apply Label Encoding and Standard Scaling for effective data preprocessing.
6. Evaluate model performance using R^2, accuracy, precision, recall, and F1-score metrics.

5. METHODOLOGY

This study employs an advanced data-driven approach to predict earthquake-induced structural behavior using machine learning techniques, particularly the Random Forest algorithm. The methodology consists of the following major steps:

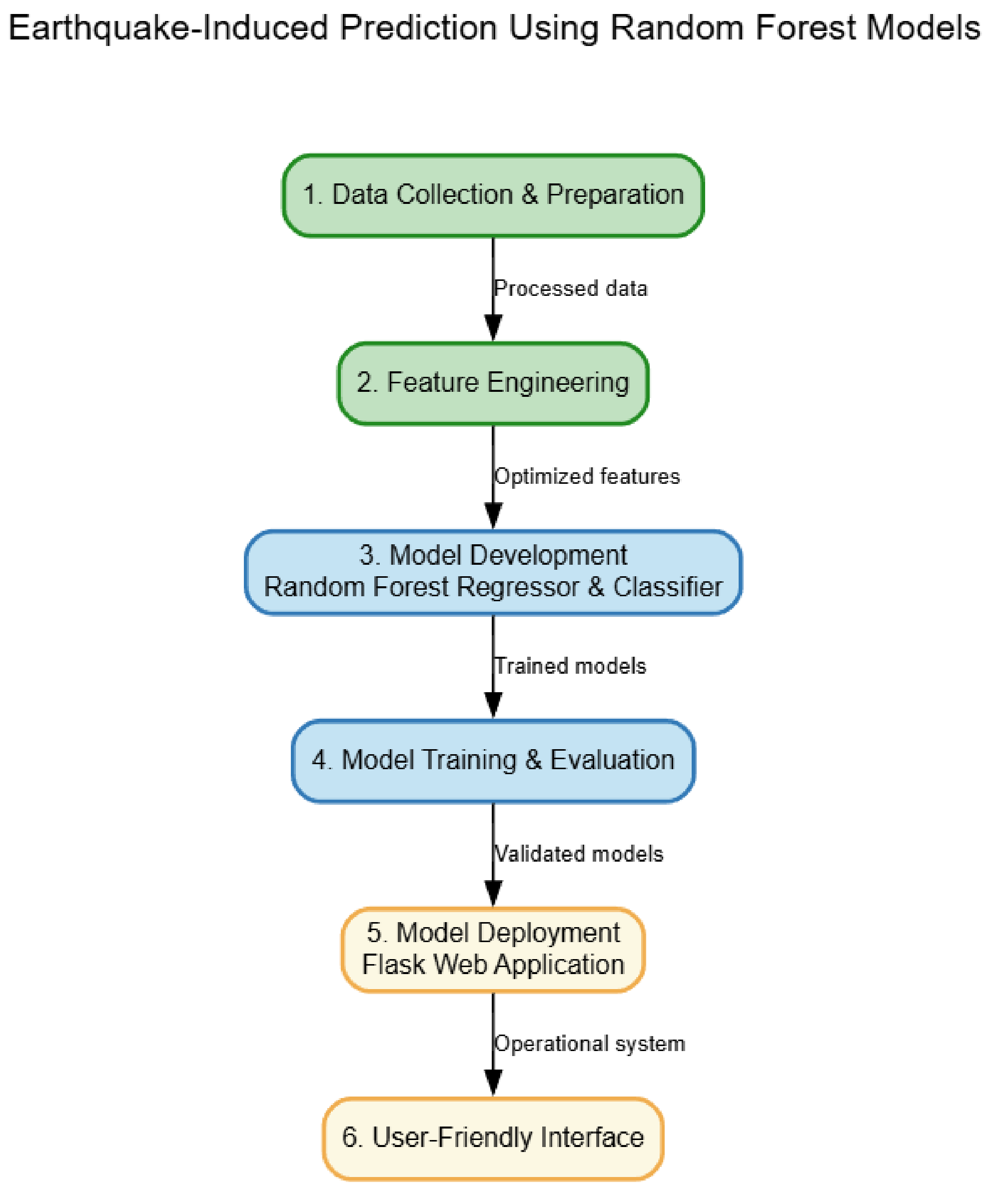


Fig 2 Methodology

1. Data Collection and Preparation

The foundation of this study lies in the collection of a comprehensive dataset, which includes crucial parameters from both building characteristics and seismic hazard conditions. The features in the dataset include Seismic Zone Classification, which categorizes the seismic risk based on geographical location; Peak Ground Acceleration (PGA), representing the intensity of seismic shaking; Building Height, the total height of the building structure; Structural Type, identifying the primary material and design of the building structure; Damper Type, specifying the type of damping mechanism used in the building; Number of Storeys, the total count of the building's floors; Damping Ratio, indicating the energy dissipation capacity of the structure; and Soil Type, classifying the type of soil at the building's foundation, which impacts seismic response. These features are selected based on their known relevance to the seismic performance of buildings. After data collection, extensive preprocessing steps are carried out. Categorical variables such as Structural Type and Soil Type are transformed using Label Encoding to convert them into numeric values suitable for machine learning algorithms. Additionally, numerical features such as Building Height and PGA undergo Standard Scaling to normalize their range and prevent model bias due to differing scales.

2. Feature Engineering

Feature engineering involves the selection of relevant variables that influence seismic performance, ensuring that the model learns the most important patterns from the data. In this study, the features selected are based on their theoretical and empirical relationships to lateral displacement, base shear force, and performance levels. These features are fed into the machine learning model to predict key seismic response parameters.

3. Model Development

The heart of the methodology lies in the development of the Random Forest models. These models are designed to predict Maximum Lateral Displacement (in mm), which is the horizontal movement of the building's structure during an earthquake; Base Shear Force (in kN), the total lateral force exerted at the base of the building; and Performance Level Classification, a categorical prediction of the building's seismic safety level, classified into three possible performance levels: Immediate Occupancy (IO), where the building is safe to occupy immediately after an earthquake; Life Safety (LS), where occupancy is not allowed, but the building is stable and no collapse is imminent; and Collapse Prevention (CP), where the building is at risk of collapse, and immediate evacuation is necessary. For the regression tasks (lateral displacement and base shear force), Random Forest Regressors are employed due to their ability to model non-linear relationships and interactions between features. For the classification task (performance level), a Random Forest Classifier is used, allowing for accurate categorization into the three predefined classes.

4. Model Training and Evaluation

The data is split into training and test sets using an 80/20 split to ensure unbiased evaluation. The models are then trained using the training dataset. The performance of each model is rigorously evaluated using various metrics: R-squared (R^2) is used for the regression models to measure the goodness of fit and prediction accuracy, with high R^2 values indicating strong predictive capabilities; while Accuracy, Precision, Recall, and F1-Score are computed for the classification model to assess its overall effectiveness and how well it predicts each performance class, ensuring high performance across all categories. Additionally, cross-validation is performed to assess the stability of the model and prevent overfitting.

5. Model Deployment

Once the models have been trained and evaluated, they are integrated into a Flask-based web application. The web application allows users to input seismic and building parameters through an intuitive graphical user interface (GUI). Users can either manually input the data or upload it in batch form using a CSV upload feature. The system then processes the input data and provides real-time predictions for Maximum Lateral Displacement, Base Shear Force, and Performance Level Classification. This easy-to-use interface ensures that engineers and stakeholders can quickly and accurately assess the seismic performance of a building based on a set of key parameters, without the need for complex simulations or expert knowledge in seismic engineering.

6. User-Friendly Interface for Decision-Making

The developed web-based tool is designed for rapid deployment in real-world engineering applications. It simplifies complex seismic assessments and makes predictive insights readily accessible to engineers, architects, and urban planners. This tool allows for quick decision-making regarding building safety, design adjustments, or retrofitting needs in seismic-prone regions.

6. DATA COLLECTION

Data Collection is a critical initial step in the process of predicting earthquake-induced displacement, shear, and performance levels. It involves gathering diverse and relevant information about both the building and seismic conditions. The data is sourced from various domains:

1. Seismic Data: This includes information on the seismic zone classification, which defines the level of seismic hazard in a given region, and the Peak Ground Acceleration (PGA), which represents the maximum acceleration recorded during an earthquake. These factors are essential for understanding the earthquake's impact on a structure.

2. Building Data: This encompasses a variety of building characteristics, such as the building's height, structural type, damping ratio, number of storeys, and damper type. These attributes significantly influence how a building responds to seismic forces and help in assessing its vulnerability and resilience.

3. Soil Data: Ground conditions, including the type of soil and soil properties (e.g., soil type and density), play a crucial role in determining how seismic waves propagate and affect the building. For instance, soft soils may amplify seismic shaking, leading to greater displacement and shear.

The collected data forms the foundation for subsequent steps, including feature engineering, model development, and predictions. The quality and accuracy of the data directly influence the effectiveness of the predictive models.

Table 1: Dataset Sample:

S. No	**Seismic Zone**	**Peak Ground Acceleration (g)**	**Building Height (m)**	**Structural Type**	**Damper Type**	**No. of Storeys**	**Damping Ratio (%)**	**Soil Type**	**Max Lateral Displacement (mm)**	**Base Shear Force (kN)**	**Performance Level**
0	Zone IV	0.149	61.1	RCC Frame	Friction	18	12.51	Hard	22.07	123.66	Immediate Occupancy
1	Zone V	0.346	92.4	Steel Frame	Friction	11	10.80	Hard	59.83	57.45	Immediate Occupancy
2	Zone II	0.337	13.1	RCC Frame	Friction	10	10.13	Soft	5.00	143.35	Immediate Occupancy
3	Zone IV	0.187	72.8	Shear Wall	Viscous	22	6.12	Medium	94.17	116.95	Immediate Occupancy
4	Zone IV	0.317	36.8	RCC Frame	Fluid Viscous	15	12.61	Hard	20.80	108.08	Immediate Occupancy
5	Zone V	0.299	93.2	RCC Frame	Viscous	19	8.52	Soft	117.72	203.36	Life Safety
6	Zone II	0.408	97.4	Shear Wall	Fluid Visco	19	2.92	Medium	333.11	170.17	Collapse Preventi

					us						on
7	Zone II	0.418	95.0	Steel Frame	Tuned Mass	19	6.07	Medium	235.07	83.75	Life Safety
8	Zone IV	0.123	52.7	Steel Frame	Tuned Mass	3	14.16	Soft	5.00	11.87	Immediate Occupancy
9	Zone III	0.287	87.6	RCC Frame	Friction	10	13.06	Soft	22.10	39.27	Immediate Occupancy

7. DATA ANALYSIS

The data collected was systematically analyzed to understand the seismic performance of various building structures equipped with different damper systems. Descriptive statistics revealed a considerable variation in seismic input, with peak ground acceleration (PGA) ranging from 0.123 g to 0.418 g across different seismic zones. Building heights varied significantly, from low-rise structures at 13.1 meters to high-rise constructions reaching 97.4 meters. A broad spectrum of damper types—including friction, viscous, fluid viscous, and tuned mass dampers—were used across different structural systems such as RCC frames, steel frames, and shear walls.

Lateral displacement, which directly reflects structural deformation during seismic events, ranged from as low as 5.00 mm in well-controlled systems to as high as 333.11 mm in high-rise buildings under severe seismic conditions. Base shear force, representing the total horizontal force experienced at the base of the structure, varied between 11.87 kN and 203.36 kN, indicating the differing dynamic response due to structural configuration, damping mechanisms, and soil conditions. Structures on soft soil showed greater displacement, while those on hard soil had lower lateral movements. Most buildings achieved the "Immediate Occupancy" performance level, suggesting minimal structural damage and high functional integrity post-earthquake. However, some cases, especially in Zone II and V with soft soils and fluid viscous dampers, recorded "Life Safety" or even "Collapse Prevention" levels, showing the critical impact of combined seismic and geotechnical conditions. The analysis highlights the importance of tailored damper selection and structural design according to the seismic zone and soil type to enhance seismic resilience.

8. EXPLORATORY DATA ANALYSIS (EDA)

As part of the data analysis process, an exploratory study of all numerical features was conducted to understand the underlying distribution and behavior of each variable. This involved visualizing the frequency distributions to identify patterns such as normality, skewness, or the presence of outliers. By analyzing these distributions, it became easier to assess the variability in structural characteristics—such as building height, base shear force, and maximum lateral displacement—and how they may influence structural performance under seismic loading.

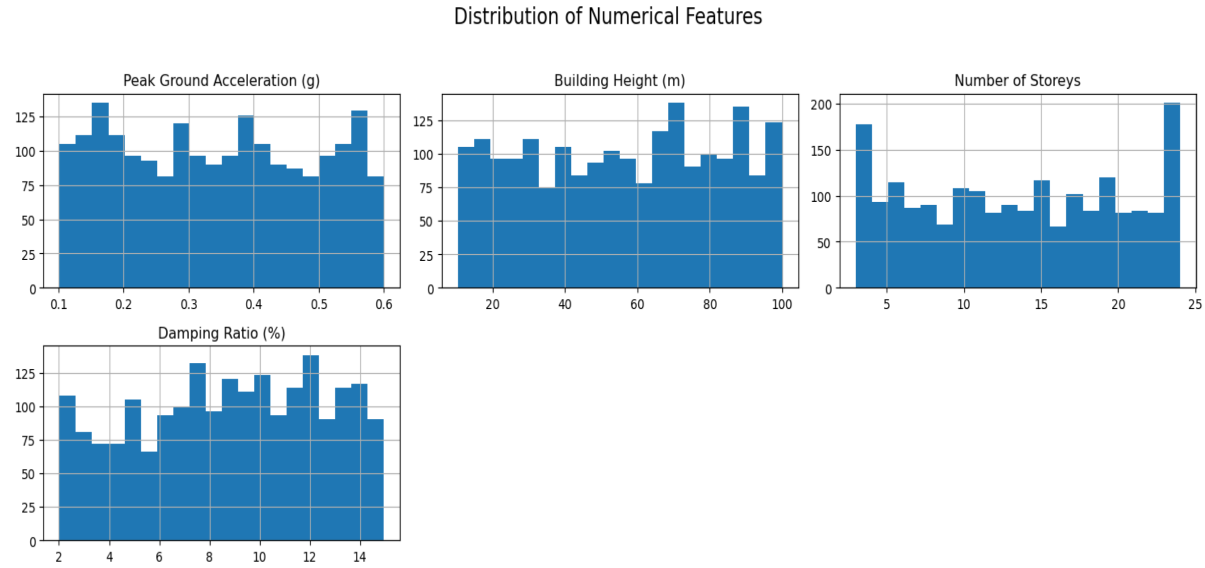


Fig 3 Distribution of the Features

The use of original category labels (such as damper type, soil type, and structural system) during this analysis ensured better clarity and interpretability of the findings. This initial visual analysis played a crucial role in guiding the next stages of data preprocessing and model development, by highlighting the need for normalization or transformation in certain cases.

Categorical Feature Distribution Analysis:

To further understand the composition of the dataset, a detailed examination of categorical features was carried out. This involved visualizing the frequency distribution of categories such as seismic zone classification, structural type, damper type, and soil type. The analysis provided insights into how often each category appeared, helping to detect any imbalance or dominance of certain classes within the data.

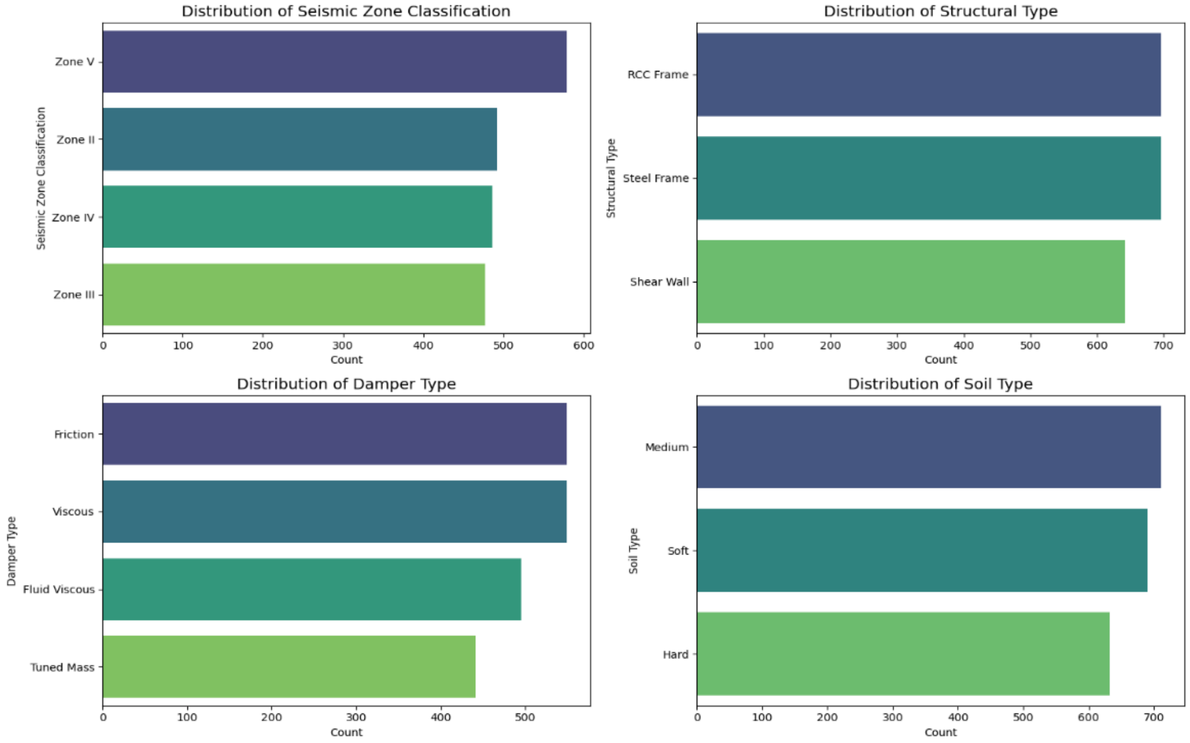


Fig 4 Categorical Feature Distribution Analysis

For instance, it was observed whether specific structural systems like RCC or Steel Frames were more commonly used in certain seismic zones, or whether particular damper technologies were favored under specific soil conditions. Such insights are crucial as they reflect real-world trends and design preferences, and also guide the selection of modeling strategies by identifying which categories are well-represented and which may require balancing or special handling during training.

Target Variable Distribution Analysis

An in-depth distribution analysis was performed on the primary target variables: maximum lateral displacement, base shear force, and performance level classification. The objective was to evaluate how these key indicators of structural performance varied across the dataset.

The distribution of maximum lateral displacement, a direct measure of how much a building sways during seismic activity, showed a wide range, indicating significant differences in structural flexibility and damping efficiency. Similarly, the base shear force distribution revealed the extent of horizontal force resisted by different building types, with values spanning from relatively low to high, depending on structural configuration and seismic intensity.

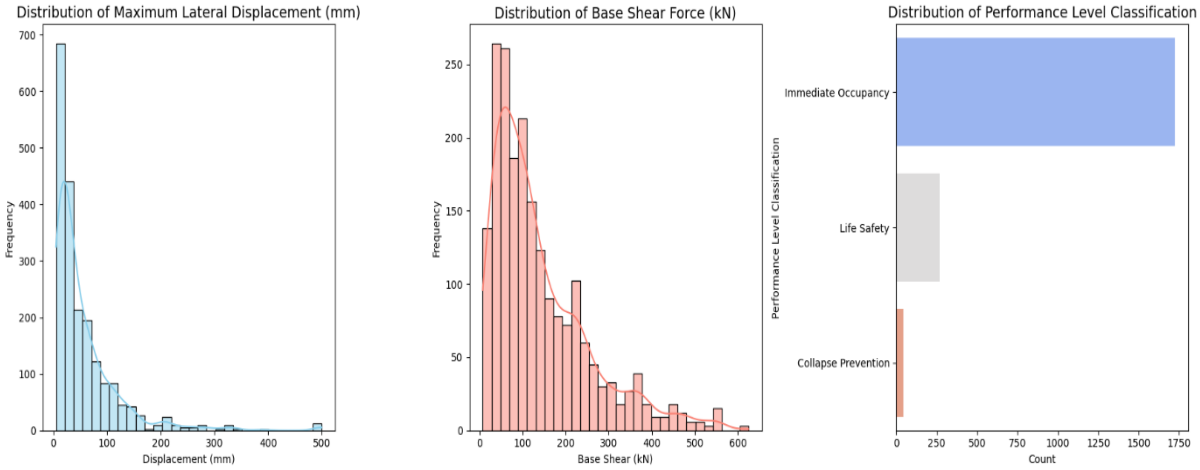


Fig 5 Target Variable Distribution Analysis

For the performance level classification, a frequency analysis highlighted the proportion of structures falling under various seismic performance categories such as “Immediate Occupancy,” “Life Safety,” and “Collapse Prevention.” This helped in identifying whether the majority of buildings met high-performance standards or whether critical vulnerabilities existed within certain categories. These insights laid the groundwork for further correlation and predictive analysis to link structural parameters to seismic resilience outcomes.

9. RESULTS AND DISCUSSION

The results of this study highlight the effectiveness of Random Forest models in predicting key seismic performance parameters for buildings under earthquake loads. The developed Random Forest Regressors for predicting Maximum Lateral Displacement and Base Shear Force, as well as the Random Forest Classifier for Performance Level Classification, demonstrated impressive performance across the board.

The Maximum Lateral Displacement model achieved an R-squared value exceeding 0.97, signifying a strong correlation between the predicted and actual values. This indicates that the model successfully captures the complex, non-linear relationship between building characteristics, seismic forces, and lateral displacement. Similarly, the Base Shear Force model also performed excellently, with an R-squared value greater than 0.97, underscoring its accuracy in estimating the forces acting on the base of the building during an earthquake.

The Performance Level Classification model exhibited near-perfect accuracy (1.0 on the test set), with excellent precision, recall, and F1-scores across all performance levels (Immediate Occupancy, Life Safety, and Collapse Prevention). This highlights the model's ability to distinguish effectively between different structural safety levels.

When compared to traditional seismic analysis methods, such as non-linear time-history analysis or finite element modeling, the Random Forest models offered a much more efficient alternative. While traditional methods are computationally intensive and time-consuming, the Random Forest approach provides rapid, reliable predictions with minimal computational overhead, making it ideal for preliminary seismic assessments and large-scale evaluations.

Furthermore, the integration of the trained models into a user-friendly web application using the Flask framework provides an accessible tool for engineers and stakeholders. The application allows users to input seismic and building data manually or upload batch files in CSV format, facilitating quick and easy seismic performance predictions. This makes the models not only highly accurate but also practical for real-world applications, enabling faster decision-making in the field of earthquake engineering.

Table 2: Maximum Lateral Displacement Model (RandomForestRegressor)

Metric	Value
Test Set RMSE	7.2582
Test Set R^2 Score	0.9879

Table 3: Base Shear Force Model:

Metric	Value
Test Set RMSE	17.0307
Test Set R^2 Score	0.9784

Table 4: Performance Level Classification Model:

Overall Accuracy

Metric	Value
Accuracy	1.0000

Classification Report

Performance Level	Precision	Recall	F1-Score	Support
Collapse Prevention	1.00	1.00	1.00	9
Immediate Occupancy	1.00	1.00	1.00	348
Life Safety	1.00	1.00	1.00	50
Macro Avg	1.00	1.00	1.00	407
Weighted Avg	1.00	1.00	1.00	407

Graphical User Interface (GUI) Development for Seismic Performance Prediction Using Flask:

The development of a user-friendly Graphical User Interface (GUI) using the Flask framework serves as a crucial component for simplifying the interaction with the seismic performance prediction models. The GUI is designed to enable users to easily input building and seismic parameters, providing a seamless experience for both experienced engineers and those less familiar with the complexities of seismic analysis. Through this web-based tool, users can quickly assess the performance of structures under various seismic conditions without needing to delve into the intricacies of machine learning or computational methods.

The interface allows users to input key parameters, such as building height, seismic zone classification, PGA, structural type, and soil type, into a series of interactive forms. For larger datasets, the GUI also supports CSV file uploads, streamlining the prediction process for multiple structures at once. Once the data is provided, the Random Forest models predict important seismic performance indicators like maximum lateral displacement, base shear force, and performance level classification.

Results are displayed instantly in a clear, easy-to-understand format, with visualizations and tables to enhance user comprehension. The web application not only provides a practical, efficient solution for quick seismic assessments but also integrates machine learning models and data preprocessing techniques to ensure accurate, real-time predictions. This tool empowers engineers, architects, and stakeholders to make data-driven decisions more efficiently, ultimately improving safety and aiding in the design and retrofitting of earthquake-resilient structures.

One of the key features of this AI-powered earthquake resilience project is the Graphical User Interface (GUI) developed using Flask. This user-friendly interface allows users to seamlessly interact with the predictive models and optimization results. Through the web-based platform, engineers, architects, and decision-makers can input critical design parameters—such as building height, seismic zone, structural type, and damping ratio—and run simulations with ease.

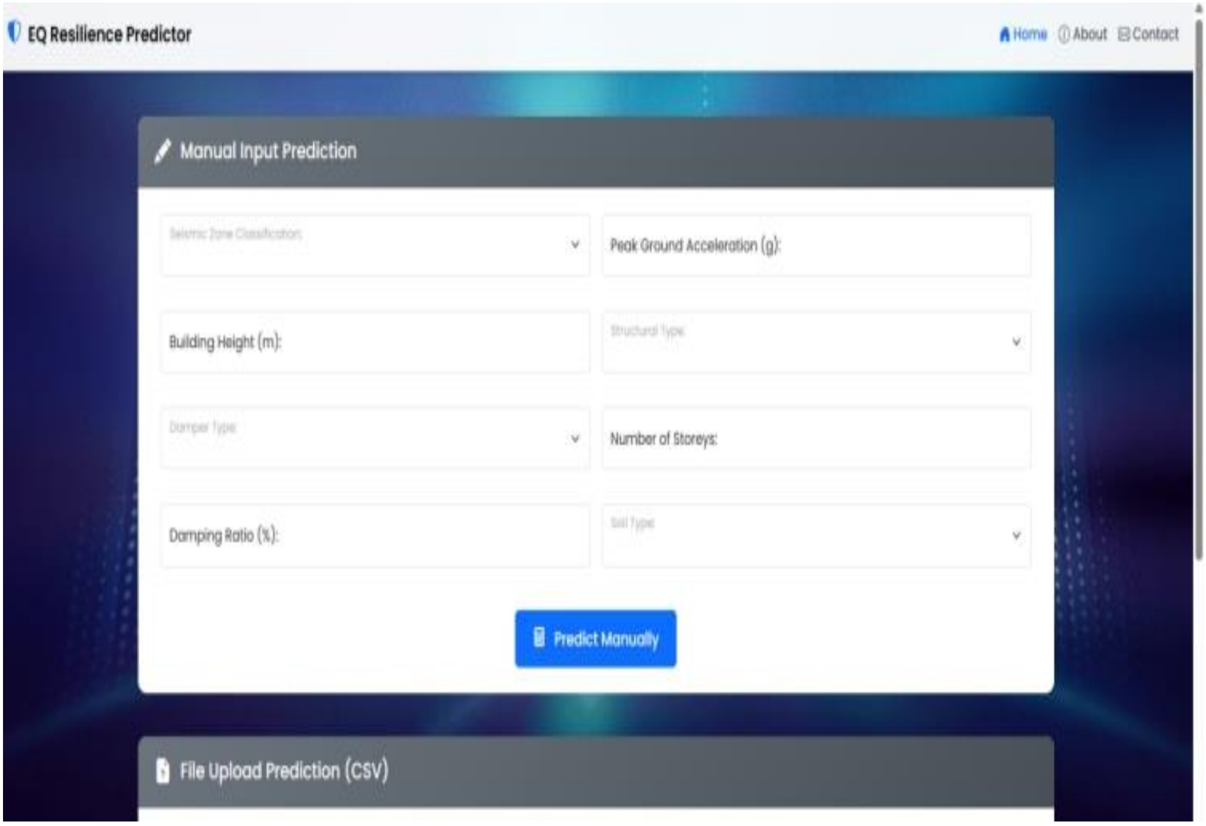
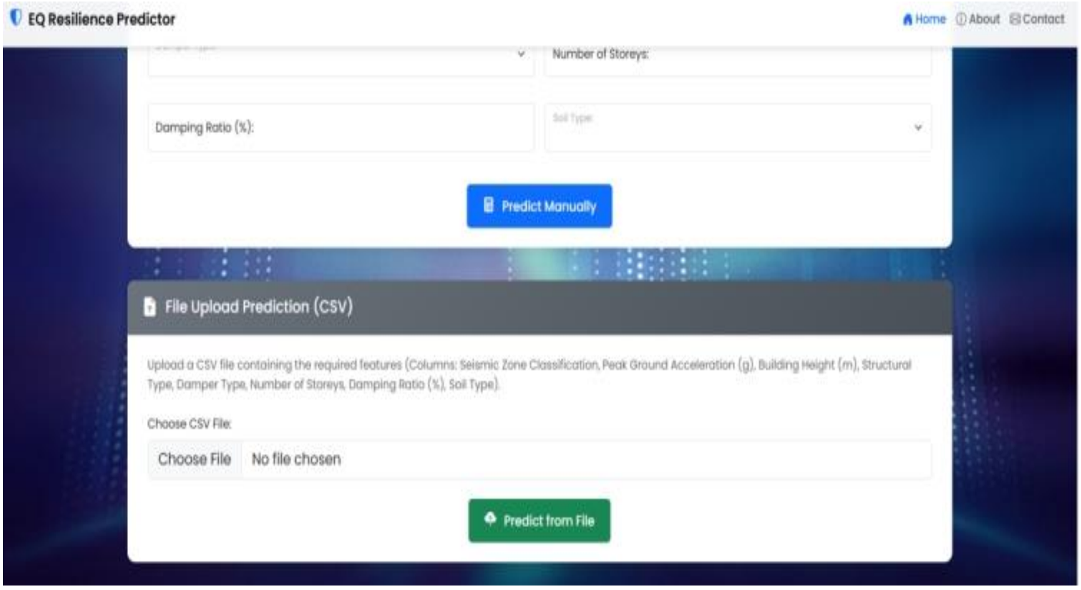


Fig 6 Index page

The Flask GUI provides real-time visualizations of seismic data, model predictions, and optimized designs, which makes it accessible to non-technical users. Users can see the impact of their design decisions through interactive graphs and tables, offering clear insights into how structural modifications may affect seismic resilience.



Number of Storeys:

Damping Ratio (%):

Soil Type

Upload a CSV file containing the required features (Columns: Seismic Zone Classification, Peak Ground Acceleration (g), Building Height (m), Structural Type, Damper Type, Number of Storeys, Damping Ratio (%), Soil Type).

Choose CSV File:

No file chosen

Fig 7 File Prediction Page

Incorporating Flask with the AI models enables dynamic decision-making, as users can fine-tune design elements based on the feedback generated by the predictive models. The system's integration with real-time simulations further empowers users to explore various design options efficiently. Screenshots of the interface can be included to demonstrate the ease of use and interactivity, showcasing how stakeholders can view seismic performance assessments and optimization results in a clear and intuitive manner.

Max Lateral Displacement: 53.41 mm

Base Shear Force: 148.87 kN

Predicted Performance: Immediate Occupancy

Fig 8 Result Page

This GUI serves as an essential tool for enhancing collaboration and improving design decisions in the context of seismic resilience.

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