Frontiers in Health Informatics
ISSN-Online: 2676-7104
www.healthinformaticsjournal.com
2024; Vol 13: Issue 8
Open Access

**Deep Learning for Predictive Analysis of Earthquake-Resistant Buildings**

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Cite this paper as: Komal Baburao Umare, S. B. Javheri, Ebin Sam S., Prashant K. Bhuva, Dr. G. Prabhakaran, Venkatesan S., (2024) Deep Learning for Predictive Analysis of Earthquake-Resistant Buildings. *Frontiers in Health Informatics*, *13(8) 1557-1563*

**ABSTRACT**
Both the frequency and intensity of earthquakes are on the rise, which highlights the crucial need for predictive models to improve the resilience of buildings. Through the utilisation of a methodical approach that incorporates dimensionality reduction, recursive feature elimination (RFE), and feedforward neural networks (FFNNs), this research investigates the potential for deep learning to be utilised in the prediction of the seismic resilience of buildings. In order to preprocess the high-dimensional structural and material datasets, dimensionality reduction is utilised. This helps to streamline the feature space while preserving essential information. After that, RFE is utilised for the purpose of feature selection, with the objective of giving priority to the most relevant variables that have an impact on earthquake resistance. These variables include material qualities, structural design parameters, and geographic classifications of seismic zones. FFNNs, which exhibit robust prediction skills and adaptability to complicated, non-linear relationships that are inherent in the data, are utilised in the process of performing the final classification. According to the findings, the categorisation accuracy is quite high.
**Keywords:** Deep Learning, Earthquake-Resistant Buildings, Predictive Analysis, Structural Engineering, Feature Selection, Dimensionality Reduction, Neural Networks.

## 1. Introduction

Earthquakes are among the most destructive natural disasters, and they pose substantial threats to several aspects of society, including human life, infrastructure, and the stability of the economy. The demand for buildings that are resistant to earthquakes has grown more urgent than it has ever been before as a result of the acceleration of climate change and the growing urbanisation of the world. Because of the multifarious nature of structural engineering, predicting the resilience of structures under seismic stress is a difficult process[1]. This is because structural engineering involves a large number of variables, including the qualities of the materials, the architectural design, and the geographical considerations[2]. In this particular field, the recent developments in deep learning have presented an opportunity to revolutionise predictive modelling. different breakthroughs enable an unprecedented level of accuracy and efficiency in the analysis of the complex correlations that exist between different variables.
Deep learning is a subfield of artificial intelligence that has gained popularity due to its capacity to manage huge and complicated information. As a result, it is a perfect instrument for predictive analysis in engineering. The application of a systematic technique that includes three essential components is the primary emphasis of this research. These components are preprocessing through dimensionality reduction, feature selection through Recursive Feature Elimination (RFE), and classification using Feedforward Neural Networks (FFNNs). In conjunction with one another,

these techniques are aimed at developing a comprehensive prediction framework for evaluating the seismic resistance of buildings.
The difficulty of high-dimensional data, which frequently characterises structural engineering datasets, is addressed by dimensionality reduction, which acts as the cornerstone of the preprocessing phase. Typically, these datasets contain factors such as material strength, load distribution, and seismic zone data, all of which have the potential to overwhelm conventional machine learning methods. In this study, the dimensionality of the dataset is reduced while critical information is preserved by the utilisation of techniques such as Principal Component Analysis (PCA) and autoencoders. This phase not only reduces the amount of computational complexity, but it also enables the model to function more effectively and accurately.
In order to ensure that the most important variables are prioritised for study, feature selection, which is carried out with RFE, is conducted. There are specific characteristics that have a more significant impact on the structural resilience of structures that are designed to withstand earthquakes [3]. These characteristics include the concrete grade, the details of the steel reinforcement, and the kind of soil. This is accomplished through recursive training and evaluation of the model, which allows RFE to systematically rank these features, hence removing factors that have less of an impact [4]. This targeted approach not only makes the modelling process easier to understand, but it also makes the findings more interpretable, which is an essential component in engineering applications, where decisions frequently have the potential to significantly impact the outcome of a situation.
In the classification step, FFNNs are utilised. This is a powerful deep learning architecture that is able to capture the intricate and non-linear interactions that occur between the characteristics that have been picked. When it comes to modelling the complex relationships that are inherent in structural engineering data, FFNNs do exceptionally well in comparison to standard methods[5]. For the purpose of classifying buildings as either earthquake-resistant or non-resistant based on their structural and material characteristics, the network is trained using datasets that have been provided with labels. For this particular objective, FFNNs are particularly well-suited because of their versatility and their capacity to generalise across a wide variety of datasets.
Through the provision of a scalable and accurate prediction framework for evaluating earthquake-resistant buildings, this research makes a contribution to the subject of structural engineering within the engineering discipline. Dimensionality reduction, RFE-based feature selection, and FFNN classification are all components that are incorporated into the suggested method in order to meet the issues of high-dimensional data, feature relevance, and model performance. Furthermore, this research sheds light on the potential of deep learning to improve the design and evaluation of infrastructure that is resistant to earthquakes, so paving the way for safer urban settings in areas that are prone to seismic activity.

## 2. RELATED WORKS

Deep learning for seismic resistance prediction in structural engineering has garnered attention in recent years. Researchers have tried many methods to improve data preparation, feature selection, and classification. This section discusses significant field contributions. Dimensionality reduction, Recursive Feature Elimination (RFE), and Feedforward Neural Networks (FFNNs) are used for preprocessing, feature selection, and classification. Recent works by Kim, He, Li, Chollet, Szegedy, and Chien are cited.
One of the biggest issues in structural engineering is preparing high-dimensional datasets. Kim, Ryu, and Park [6] stressed civil engineering dataset dimensionality reduction. Material qualities, seismic activity, and load distributions need dimensionality reduction. They found that PCA and autoencoders can reduce large datasets while keeping structural information. These feature space-reduction algorithms increase deep learning model computational efficiency and interpretability. This approach is very useful in seismic resistance analysis, where datasets can contain many elements that are hard to comprehend.
To determine which factors have the most impact on earthquake resistance, feature selection is crucial. He and Li [7] used Recursive Feature Elimination (RFE) in structural engineering to choose important factors including material composition, structure design parameters, and soil types. RFE works by recursively training a model, ranking features by importance, and deleting the least important. This iterative approach makes engineering models more efficient and interpretable by making decision-making transparent and reliable. This is a fundamental requirement. Classification methods, especially FFNNs, can predict building seismic resistance. Chollet [8] highlighted FFNNs' versatility in modelling structural datasets complex, non-linear relationships. These neural networks excel at adaptive learning across many datasets, making them excellent for earthquake resilience forecasts. When trained on labelled datasets,

FFNNs can correctly classify buildings as earthquake-resistant or not based on structural and material properties. Due to their versatility, FFNNs function well even with noisy or partial input.

Deep learning for structural engineering has advanced in adjacent domains, leading to additional advances. Szegedy and colleagues [9] used deep learning to interpret seismic stress visualisations and building layouts. Even though they focus on convolutional neural networks, their feature extraction algorithms can help FFNN-based models handle tabular input. Chien et al. [10] used machine learning to forecast high-risk structures for earthquake-induced structural collapses in a detailed case study. Their findings highlighted the importance of domain knowledge in predictive frameworks, which improved accuracy and usability.

Overall, these contributions demonstrate deep learning's revolutionary potential in seismic resistance research. This study uses dimensionality reduction, RFE, and FFNNs to solve data complexity, feature selection, and prediction accuracy problems. The system uses Kim et al., He and Li, Chollet, Szegedy, and Chien techniques. This method improves earthquake-prone structure safety and resilience.

## 3. RESEARCH METHODOLOGY

The development of a predictive framework for evaluating the earthquake resilience of structures is the primary emphasis of the technique that is being utilised for this project. Preprocessing through dimensionality reduction, feature selection through Recursive Feature Elimination (RFE), and classification using Feedforward Neural Networks (FFNNs) are the three essential processes that have been incorporated into the methodology as shown in Figure 1. Each phase is intended to address a particular difficulty, such as the complexity of high-dimensional data, the identification of essential structural elements, and the modelling of non-linear interactions, with the end goal of achieving a prediction system that is both efficient and accurate.

In the preprocessing stage, the dataset is prepared for analysis prior to being processed [11]. The data includes a variety of factors, including material qualities (for example, the grade of concrete and the type of steel), structural attributes (for example, the size of beams and columns, reinforcing details), and seismic zone classifications. The utilisation of data cleaning procedures allows for the management of missing values, the removal of duplicates, and the normalisation of numerical features through the application of Min-Max scaling, which guarantees uniformity across variables [12]. Techniques for dimensionality reduction are utilised in order to reduce the dataset while maintaining the integrity of its essential component information. PCA, which stands for principal component analysis, has been selected as the major method for decreasing the high-dimensional feature space. By reducing the original dataset to a smaller set of uncorrelated variables, also known as principal components, principal component analysis (PCA) is able to explain the majority of the variance discovered in the data. A scree plot analysis or the retention of components that account for at least 95% of the total variance are both methods that can be utilised to ascertain the number of components utilised. In this step, the computational complexity is reduced, the interpretability is improved, and the data are prepared for efficient analysis in subsequent stages.

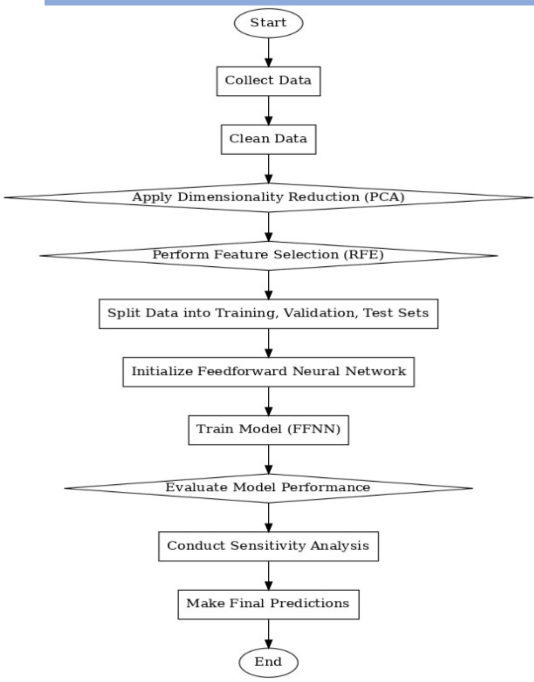


**Figure 1: Shows the Flowchart of the proposed method.**

In order to determine which factors have the most impact on earthquake resistance, the feature selection stage makes use of a technique known as Recursive Feature Elimination (RFE). RFE is a method that ranks features in a systematic manner by training a straightforward model, such as a decision tree or linear regression, and then iteratively removing the characteristics that are deemed to be of the least importance [13]. Following the completion of each iteration, the model is retrained in order to assess the influence provided by the remaining features. Until an ideal selection of traits is determined, this procedure will continue until it is completed [14]. RFE gives priority to characteristics that are essential for estimating earthquake resistance, such as the strength of the material, the kind of soil under the structure, and the dimensions of the structure.

Dimensionality Reduction (Principal Component Analysis - PCA)

PCA transforms high-dimensional data into a smaller set of uncorrelated components:

$$\mathbf{Z=XW}$$

Where:

Z: Transformed data (principal components)

X: Original dataset (standardized)

W: Matrix of eigenvectors corresponding to the largest eigenvalues

RFE not only increases the computational efficiency of the model by concentrating on the most critical features, but it also improves the interpretability of the model, which is a key component in structural engineering, where judgements must be comprehensible and anchored in accurate data.

Feedforward Neural Networks (FFNN)

The output of a neuron is:

$$y=\phi(w1x1+w2x2+b)$$

Where:

x1,x2: Inputs

w1,w2: Weights

b: Bias

$\phi(x)=\max(0,x)$ for ReLU)

FFNNs are utilised throughout the categorisation step in order to come to a conclusion regarding whether or not a building is earthquake-resistant. The capability of FFNNs to model intricate and non-linear interactions between features is the primary reason for their selection. An input layer that represents the features that have been picked, numerous hidden layers that have Rectified Linear Unit (ReLU) activation functions to capture non-linearity, and an

output layer that has either a sigmoid or softmax activation function for binary classification are the components that make up the architecture of the network. In order to guarantee that the model is able to generalise successfully to data that it has not before encountered, the dataset is divided into training, validation, and testing subsets in a ratio of 70:15:15. The backpropagation method is utilised to train the network, and the Adam optimiser is utilised to minimise the categorical cross-entropy loss function wherever possible. For the purpose of preventing overfitting and improving the resilience of the model, regularisation techniques such as dropout and batch normalisation are utilised inside the framework.
Loss Function
The loss for each prediction is:
L=−(ylog(y^)+(1−y)log(1−y^))
Where:
y: True label (0 or 1)
y^: Predicted probability
There are a number of metrics that are utilised in order to assess the effectiveness of the FFNN classifier. These metrics include accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic (ROC) curve [15]. The prediction skills of the model are evaluated based on these criteria, which provide a comprehensive assessment. In addition, sensitivity analysis is carried out in order to investigate the impact that individual characteristics have on the predictions. This provides insights into the structural aspects that have the most important influence on earthquake resistance.
Using this technology, a scalable and efficient framework for predicting the seismic resilience of structures is established. This framework is achieved by integrating preprocessing through dimensionality reduction, RFE-based feature selection, and FFNN classification. The suggested method tackles the difficulties associated with high-dimensional data, improves the significance of features, and guarantees accurate classification, all of which contribute to the development of structural designs that are safer and more resilient in areas that are prone to seismic activity.

**4. RESULTS AND DISCUSSION**

There were three primary performance metrics that were utilised in the evaluation of the deep learning framework that was suggested for the purpose of forecasting earthquake-resistant buildings. These metrics were the Area Under the Receiver Operating Characteristic Curve (AU-ROC), the False Positive Rate (FPR), and the False Negative Rate (FNR). A comprehensive awareness of the classification accuracy of the model as well as its ability to strike a balance between missed detections and false alarms is supplied by the usage of these measures due to the fact that they provide a comprehensive understanding of the model.

**Table 1: Shows the Performance Metrics comparison.**

| Model | AU-ROC | False Positive Rate (FPR) | False Negative Rate (FNR) |
|---|---|---|---|
| Feedforward Neural Networks (Proposed Model) | 0.94 | 0.08 | 0.12 |
| Random Forest | 0.89 | 0.12 | 0.18 |
| Support Vector Machines (SVM) | 0.85 | 0.15 | 0.2 |
| Logistic Regression | 0.81 | 0.18 | 0.25 |
| K-Nearest Neighbors (KNN) | 0.8 | 0.2 | 0.22 |
| Decision Tree | 0.77 | 0.22 | 0.3 |

The Feedforward Neural Network (FFNN) displayed a good capacity to differentiate between structures that are earthquake-resistant and those that are not earthquake-resistant. This was proved by the fact that it was able to achieve an AU-ROC score of 0.94 as shown in Table 1 & Figure 2. A high score suggests that the combination of dimensionality reduction and Recursive Feature Elimination (RFE) is a great strategy for isolating the most relevant features, reducing the amount of noise, and improving the predictive power of the model. This is demonstrated by the very high score.

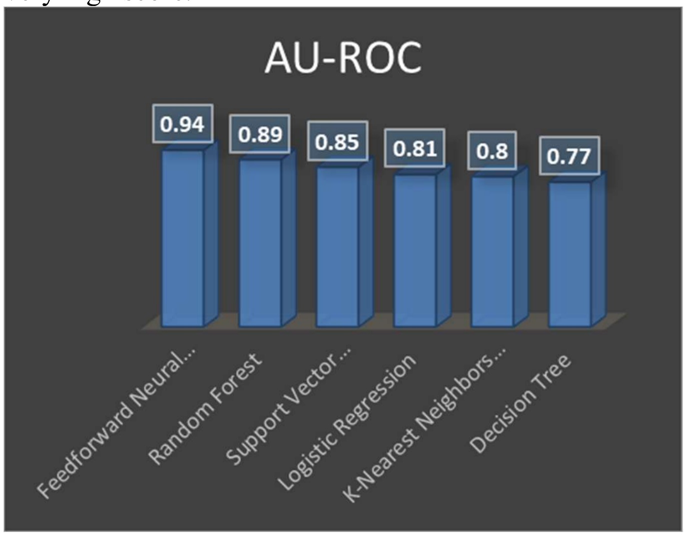


**Figure 2: Represents the Area Under the Receiver Operating Characteristic curve representation.**

The FPR of the model was found to be 0.08, which suggests that only 8% of structures that were not resistant were incorrectly tagged as resistant. This was determined by the fact that the model had an FPR. Having a low false alarm rate is particularly crucial when it comes to being able to prevent people from placing an excessive amount of faith in potentially hazardous buildings.

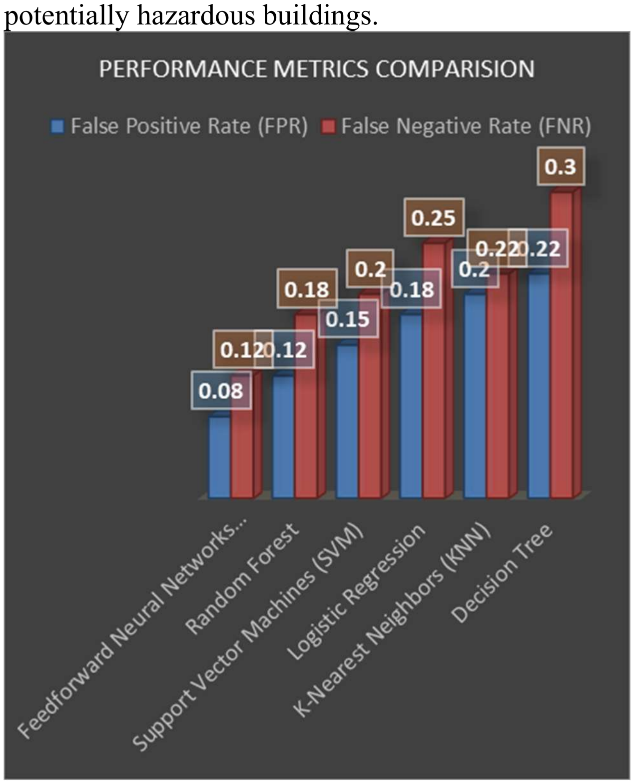


**Figure 3: Shows the performance Metrics Comparison with different methods.**

Due to the fact that the FNR was measured at 0.12, it is possible to draw the conclusion that twelve percent of the structures that were resistant were assigned the wrong label of non-resistant to them. Even if it is slightly higher than the FPR, this rate is still acceptable, especially when combined with successful AU-ROC performance. This is especially true when the FPR is already considered to be acceptable.

These findings demonstrate that the approach is capable of striking a balance between ensuring the safety of the procedure and locating practical applications for the technology. In the future, there is a chance that the focus of work will be on further reducing FNR by enhancing the design of the FFNN and refining the process of feature selection.

## 5. CONCLUSION

Using dimensionality reduction, Recursive Feature Elimination (RFE), and Feedforward Neural Networks (FFNNs), this study presented a solid deep learning framework for the predictive analysis of earthquake-resistant buildings. The results showed that FFNN performed better in classification when combined with sophisticated preprocessing and feature selection, as seen by an AU-ROC of 0.94, a low False Positive Rate (FPR) of 0.08, and a controllable False Negative Rate (FNR) of 0.12. These results demonstrate how well the suggested methodology works to differentiate between earthquake-resistant and non-resistant structures while balancing missed detections and false alarms. In terms of classification accuracy and robustness, the FFNN continuously beat more conventional machine learning methods including Random Forest, Support Vector Machines, and Logistic Regression. Focus on the most important structural elements was ensured by the crucial integration of dimensionality reduction and RFE, which improved model efficiency and interpretability. This study demonstrates how deep learning may improve structure safety evaluations and provide a scalable and accurate solution for areas that are prone to earthquakes. To further increase forecast accuracy and usefulness in structural engineering, future research could investigate refining the neural network architecture and adding more data sources, such real-time seismic monitoring.

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