Journal of Information Systems Engineering and Management
2025, 10(24s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Integrating Artificial Intelligence in Earthquake-Resistant Structural Design - Advances in Sustainable Building and Concrete Technology

Amitava Sil[a*], Shiv Shankar Kumar[b], Sourav Dandapat[c]
[a*]*Scientist, IWST Field Station, Kolkata*
[b]*Department of Chemical Engineering, IIT Madras*
[c]*B.Tech in Civil Engineering, Asansol Engineering College, West Bengal*
Corresponding Author: ***Amitava Sil***

ARTICLE INFO

Received: 18 Dec 2024

Revised: 05 Feb 2025

Accepted: 18 Feb 2025

ABSTRACT

Smart building management and construction is tremendous for developing smart cities in building sites and is known for its stability and durability. However, its performance can be significantly enhanced by improving material properties such as strength, fire resistance and impact protection. Conventional earthquake structural design considers only a limited number of factors, mainly elastic structural properties, to determine the critical design parameters.Yet, these parameters are often suboptimal since they do not consider the extensive plasticity expected in building structures during earthquakes. One significant challenge in concrete design is that it is difficult to predict the exact performance of a particular concrete mix without extensive testing, which is time-consuming and costly.Conventional techniques for optimizing concrete properties depend significantly on empirical testing and expert intuition, which are time-consuming and may not completely handle the complex interactions among various material components.To address the above problems, this research presents the Artificial Intelligence (AI) based Multi-Layer Perceptron Neural Network (MLPNN) method for efficient building construction that resists earthquakes.To start with the proposed work, C-Score Normalization (CSN) method is employed to normalize the collective dataset. Then, select essential features of concrete materials using the Deep Feature Elimination with Residual Network (DFE-RN)approach. Following that, the MLPNN method is used to classify the best materials for efficient building construction that resists earthquakes. The proposed framework has the potential to revolutionize the building industry by constructing concrete with improved properties, reducing the need for extensive physical testing and speeding up the innovation process.This paper demonstrates the proposed AI-based approach can effectively improve Earthquake-resistant structural design. The proposed simulation result illustrates the efficient performance regarding precision, recall, classification accuracy and F1-score with less time complexity.

Keywords: Building construction, classification, concrete, earthquake, pre-processing, feature selection, material components,structuraldesign.

1. Introduction

Civil engineers must prioritize designing buildings that are earthquake-resistant since earthquakes are a severe hazard to infrastructure and human life. Seismic occurrences during the past century have left extensive damage in their wake, highlighting the necessity of robust infrastructure that can endure ground shaking. Reducing the destructive impact of earthquakes on structures and communities has been the driving force behind the development of earthquake engineering [1]. The stability of infrastructure and structures around the world is seriously threatened by earthquakes, which are erratic and destructive natural events. Given the growing urbanization in seismically active areas, the need to produce materials resistant to earthquakes has never been more pressing [2].Classifying the several facets of seismic engineering, such as different building materials, tracking the condition of building components or structures, and predicting their seismic resistance, was the author's goal

[1]. An approach known as Machine Learning (ML) was used to achieve the goal. If the data is biased, erroneous, or incomplete, the AI system's performance will suffer. Because of this dependency, applying machine learning in fields with limited or difficult-to-get quality data is challenging. To fix the problem, the [2] used a K-Nearest Neighbor (KNN) technique. However, the experience of the engineering reconnaissance team is the only factor that determines the risk statuses of structures, therefore typical conclusions may not be possible.

Accurately classifying infrastructure systems with diverse properties, including conditions, materials, surface appearances and textures, was the author's [3] goal. A Convolutional Neural Network (CNN) approach was used to achieve the goal. The CNN isn't strong enough to handle this kind of variability, though. A Random Forest (RF) approach was used to fix the problem. Rapidly determining the extent and spatial distribution of building damage is crucial for emergency response and recovery following an incident. However, RF required more processing power and was more complicated [4].

Cement is the primary component of concrete, a substance used extensively in buildings, according to the author [5]. Because of the numerous gases released during cement production and use, the environment is negatively impacted. A technique called AdaBoost was used to categorize the mechanical characteristics of the concrete. If the number of boosting iterations is too high or the weak classifiers are too complicated, the suggested approach, however, results in over fitting. To fix the problem, the author used an improved ML technique [6]. Therefore, there was insufficient labeled data to train and validate the model on a wide scale. Artificial Intelligent such as SARIMA, multi-variable regression, ridge regression, and KNN regression for prediction water level[7].

To find structural deterioration, the author [31] used an unsupervised DL-based method. For its training procedures, it needs data from a structure that is intact as well as different damage scenarios of structures that are being observed. Labeling the training data, however, is usually expensive and time-consuming. The author used an improved RF technique to fix the problem [8]. The suggested model is adaptable enough to take into consideration more experimental findings that provide fresh perspectives. However, because RF can be unstable, even a small change in the training data might have a significant impact on the final model.

The efficacy of current ML-based damage identification techniques is mostly reliant on the chosen signatures from raw signals, according to the author [9]. As a result, it might not perform as well in other situations. The Deep CNN (DCNN) approach was used to fix the problem. It was utilized to locate and identify damage to building structures that have smart control devices installed. The time-consuming nature of DCNN, however, might have an impact on real-time performance in real-world applications. Gradient Boost Regressors (GBR) and XGBoost technology were used to fix the problem. Therefore, using standard linear or nonlinear regression studies to predict the compressive and flexural strengths of SFRC is challenging [10].

In order to forecast the compressive strength of concrete, the author [11] used an innovative approach that utilized ML. By combining multiple weak learners, this method uses the adaptive boosting algorithm to create a strong learner that can identify the mapping between the input and output data. Accurately predicting the compressive strength of concrete material is difficult, though, because of this complex system. An improved GBR with XGBoost (GBR-XGB) technique was used to fix the problem. However, because each classifier must correct the mistakes made by the previous learners, GBR-XGB was extremely sensitive to outliers [12].

An ensemble ML methodology was used by the author [13] to estimate the modulus of elasticity of concrete made from recycled concrete aggregate in response to mixture design characteristics. Even if the basis classifier accuracy is low, high accuracies can be obtained if distinct base models incorrectly categorize different training samples when ensembles are utilized for classification. A Hybrid Ensemble Model (HENSM) was used to fix the problem. The HENSM has been found to generate more accurate predictions. However, because several models had to be trained, stored, and their outputs combined, HENSM was time-consuming [14]. A Multi-Objective Optimization (MOO) approach was used to address the problem. Prior to the construction phase, the MOO model can be used as a design guide to help with decision-making. Most of the time, nevertheless, it is necessary to optimize several goals at once [15].

To support sustainable development and lessen its impact on the environment, the construction sector must improve seismic design and switch from strength-based to damage control-based, creative structural solutions [16]. The main goals of seismic design are to minimise damage to buildings so they won't collapse during strong earthquakes, guarantee utility and safety, and integrate clever framing techniques for important structures

[17]. With appropriate design and construction, earthquake-resistant components increase a structure's seismic resistance, reducing damage and fatalities in high-rise buildings [18]. Advances in the multidisciplinary field of earthquake-resistant structure design include performance-based codes, probabilistic analysis, and enhanced analytical tools. Deterministic methods are anticipated to be replaced by this field [19].

During the Ahmedabad earthquake, many reinforced concrete frame structures were severely damaged or collapsed. The Sabarmati River left behind deep sediments on which many buildings were built. Such buildings might have felt more ground motion as a result of this. Inadequate structural design and poor construction were other significant contributor to the destruction. To solve the aforementioned issues, a case study of an earthquake-damaged structure in Bhuj was conducted. This study introduces the Artificial Intelligence approach to effective earthquake-resistant building construction.

AI models, especially Multi-Layer Perceptron Neural Networks (MLP-NN), hold the potential for this process since, using large databases, relationships between interdependent parameters can be modeled at a level that has not been possible earlier. This approach thereby enables multi-objective optimization using historical data, domain knowledge, and real-time data inputs to supply useful information to engineers. The MLP-NN also has high-quality performance in noisy and incomplete data; therefore, it is highly applicable in real-life construction practicality and resiliency to earthquakes. The incorporation of these AI-driven methods initiated herein for sustainable construction is thus a revolution, responding to the environmental issues of concrete production and issues of seismic stability of buildings in regions with high risks of earthquake. This paper provides valuable recommendations for improving the role of AI in this field, thus ensuring a sustainable and safe construction environment is provided.

When discussing earthquake-resistant building design advances, Mohammad Shahjalal *et al.* [20] place a strong emphasis on cutting-edge materials, technologies and techniques. For better seismic performance, it highlights the significance of shape memory metals, fiber-reinforced plastics, and artificial intelligence. An AI model for effective earthquake-resistant building design is presented by Behera *et al.* [21]; it predicts design parameters with reduced calculation time, showing promise for further study and use. According to Plevris *et al.*,[22] artificial intelligence (AI) has the potential to reduce earthquake risk through dynamic multi-hazard risk assessments, real-time structure health monitoring, and early warning systems.

The conventional view of concrete as a static, unchangeable material has given way to a dynamic field characterized by ongoing innovation within this dynamic environment [23]. The concept of sustainable and long-lasting concrete has changed over time, reflecting the paradigm shifts in contemporary buildings [24,25]. Sustainable cementitious materials, such as calcium sulpho-aluminate cement and alkali-activated binders, are among the notable advances [26,27]. By lowering the carbon footprint of concrete, these materials have the potential to transform construction methods completely [28-30]. However, there is still a need for more research as these new materials become available. A novel method is needed to increase the sustainability of concrete buildings in order to lessen the environmental impact of concrete used in businesses [3–4]. One of the newest and most important topics in both academic research and engineering practice is Artificial Intelligence (AI). The field of computer science that creates software and machines with intelligence similar to that of humans is called AI. AI methods have spread quickly in recent years and are now widely used in several engineering specialties [5].

2. Materials and methods

This section demonstrates the detailed process of earthquake-resistant intelligent structural design of building materials using an AI-based approach. Figure 1 describes the proposed architecture diagram for the earthquake-resistant intelligent structural design. Initially, the dataset was gathered from the Kaggle repository. It contains nine columns: cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, fine aggregate, Age (day), and concrete compressive strength.

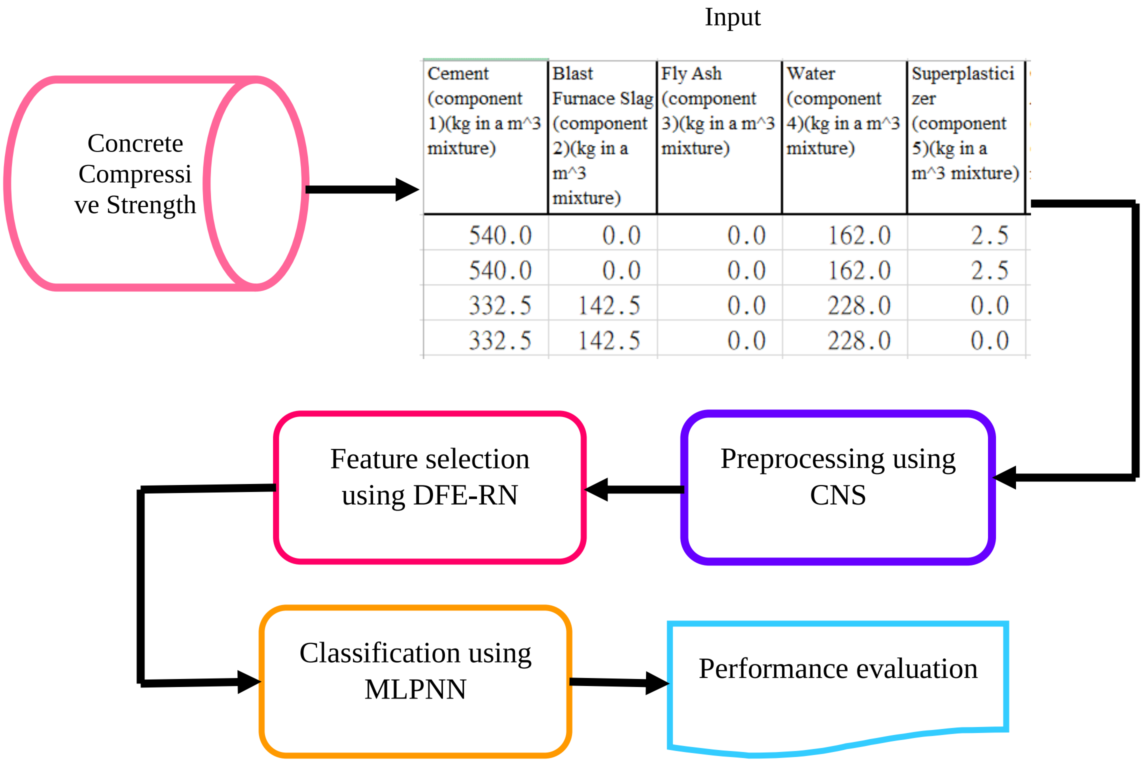

Fig 1: Architecture diagram for earthquake-resistant intelligent structural design

Next, the CSN method is employed to normalize the collective dataset. Then, the essential features of concrete materials will be selected using the DFE-RN approach. Following that, the MLPNN method is used to classify the best materials for efficient building construction that resists earthquakes.

2.1 C-Score Normalization Method

C-Score Normalization is a statistical process of scaling and normalizing data for modeling when one is working with the datasets on earthquake building damage predictions. This method brings raw input values into the same range so that none of the features can overpower other variables because they are more prominent in magnitude. The specific computation form of C-Score Normalization is to obtain the feature's normalized value based on the value's deviation from the population's mean, with a constant calibrated factor. The proposed method makes sure that a quantitative attribute such as 'asphalt, brick, timber and bamboo, etc.,' makes the same contribution to the model as a discrete attribute such as 'soil type.' This method is beneficial for preprocessing the earthquake data set so as to enhance the efficiency of pattern recognition for damage prediction by AI-based DL algorithms. Equation 1,2,3 illustrates the C-Score normalization formula,

$$C_x = \frac{I_x - \mu}{\sigma} \quad (1)$$

Let's assume I_x as the data point, x as the sample, I as the actual value, μ as the mean of the feature values, and σ as the standard deviation of the feature values in the dataset.

$$\mu = \frac{1}{N}\sum_{x=1}^{N} I_x \quad (2)$$

Here, N represents the total number of samples in the earthquake building damage prediction dataset.

$$\sigma = \sqrt{\frac{1}{N}\sum_{x=1}^{N}(I_x - \mu)^2} \quad (3)$$

These equations remove feature scale differences, improve model convergence in DL methodologies, and enhance the interpretability of features' contributions. By following equation 4 C-Score was adjusted to normalize the bound between two specific values (0to1).

$$C_d = \frac{C_x - \min(C)}{\max(C) - \min(C)} \quad (4)$$

Let's assume, C_d is adjusted C-Score for the data point, $\min(C)$ as the minimum score value in the used dataset, and $\max(C)$ as the maximum score value in the used dataset. It is used to adjust all normalized values to fall within a specific range, making them more interpretable for prediction models. Here I_x contains structural integrity, distance from the epicenter, soil type, building material, and other related factors. C_x is used to focus on the relative contribution of each feature, eliminating the influence of varying scales. J is illustrated for building damage severity levels (e.g., no damage, moderate damage, severe damage). Equation 5 predicts the model example,

$$J = f(C_d, U) + \varepsilon \quad (5)$$

Let's assume, J is damage level prediction, C_d is adjusted input factors, U is the model weight for feature importance, and ε is the error term. The normalized dataset shows that feature distributions are more aligned with each other, removing noise and highlighting essential patterns. This has enabled better prediction when AI is coupled with the DL model to improve the identification of high-risk buildings. The preprocessing step, C-Score Normalization, enables a cost-effective method of both earthquake damage assessments and disaster risk mitigation regarding management and resource allocation, infrastructure, etc.

2.2 Deep Feature Elimination with Residual Network (DFE-RN)

After preprocessing the predicted building damage from the earthquake dataset, the DFE-RN method was used to select the appropriate features. DFE-RN is useful for reducing the number of features in the data set, which makes the processes enhanced and more specialized. Residual connections mitigate the vanishing gradient problem, improve the network's ability to learn complex features, and enhance prediction accuracy. Subsequently, using DFE, the most relevant features from a building damage point of view (e.g., brick, wood, soil type) may be analyzed. The obtained reduced dimensionality vectors are applied to the ResNet model for learning to compute in residual blocks prediction of building damage while still preserving essential features and learning higher level features at deeper levels. Using the identified features of the earthquake, the DFE-RN produces the predicted damages, including the levels or probabilities. Equation 6 eliminates the irrelevant features,

$$X(f_y) = \frac{1}{N}\sum_{x=1}^{N} \Delta\mathcal{L}(f_y \backslash G_x) \quad (6)$$

Let's assume, that f_y is the feature, $X(f_y)$ is the importance of f_y, G_x is the subset of the dataset, $\Delta and\ \mathcal{L}(f_y \backslash G_x)$ is the loss difference when f_y is excluded. Features with$X(f_y) < \tau$ (threshold τ) are iteratively removed to refine the input data. After refining the input data, the ResNet was performedat equation 7,

$$j = F(i, \{U_x\}) + i \quad (7)$$

Let's assume, i as the input to the residual block, j as the output block, U_x weight, and $F(i, \{U_x\})$ as the transformation function with U_x. This equation is used to learn hierarchical feature representations for predicting building damage. It combats vanishing gradients and facilitates learning by adding shortcut connections. Equation 8 combines DFE and ResNet to improve the accuracy and efficiency,

$$\hat{j} = Softmax\left(h\left(F_R\big(D(I)\big)\right)\right) \quad (8)$$

Let's assume, $\widehat{}$ that j is the predicted class, h is the fully connected layers for classification, F_R is the feature extraction and learning via ResNet, ( )and DI is the processed features via the elimination stage. This equation integrates feature elimination and ResNet for improved accuracy and efficiency. By following, the loss function was performed through the equation 9,

$$\mathcal{L} = -\frac{1}{S}\sum_{x=1}^{S}\sum_{y=1}^{K} j_{x,y} \log(\hat{j}_{x,y}) \quad (9)$$

Let's assume $\mathcal{L}$ as cross-entropy loss, S as the number of samples, K as the number of classes, $j_{x,y}$ as the ground truth label and $\hat{j}_{x,y}$ as the predicted probability. This method is optimized for the accuracy, scalability, and computational cost necessary for a large-scale damage prediction application. The results prove the model's applicability in managing the risks associated with disasters and the recovery phase following earthquakes by accurately and quickly predicting the levels of building damage.

2.3 Multi-Layer Perceptron Neural Network (MLPNN) method

The MLP-NN classification method is also a supervised AI-based DL technique used to predict the degree of building damage from data from an earthquake catastrophe. This MLP-NN method uses input features from a preprocessed dataset to transform them into output classifications (for instance, undamaged, minor, moderate, and major damages). The input layer takes in the attributes of an earthquake, including magnitude, distance to the epicenter, type of soil, age of building and material and structural construction. The hidden layer, which contains neurons, is fully connected and gives a non-linear transformation to the input data. The ReLU activation function is used to analyze dependencies between features. The output layer, on the other hand, provides the classification of the level of building damage. A SoftMax activation function is often used in the case of multi-class classification. During the training process, the network is trained with a backpropagation algorithm with an optimization function based on a loss function such as cross-entropy. The training phase of the model deemphasizes patterns on labeled examples that are available in the training set. Therefore, based on the earthquake damage dataset, MLP-NN can be used to predict building damage and help move and mitigate the risk indicators. Equation 10 provides the transformation from the input layer to the hidden layer in the multi-layer MLP-NN,

$$q_y = \sum_{x=1}^{n} u_{xy}.i_x + b_y \quad (10)$$

Let's assume, y is the neuron, q_y is the weighted sum for the y in the hidden layer, x is the input feature, i_x is the x from the dataset (e.g., building age, material, location), u is the weight of the input features and b as bias term. This equation processes earthquake features (e.g., building attributes) and learns complex relationships using weights, biases and activation functions. The activation function ReLU and Sigmoid was performed through the equations 11 and 12,

$$z_y = \max(0, q_y) \quad (11)$$

$$z_y = \frac{1}{1+e^{-q_y}} \quad (12)$$

Here z_y represents the output of the activation function for the y.An activation function introduces non-linearity to the network, enabling it to learn complex patterns. The hidden layer to output layer transformation was performedthrough equation 13,

$$j_c = \sum_{y=1}^{S} u'_{yc} . z_y + b'_c \quad (13)$$

Let's assume, j is the weighted sum, c is the output class (e.g., "No Damage," "Minor Damage," "Severe Damage"), u' as the weight of the classification attributes and b' is the bias term. This equation produces probabilities of damage levels using SoftMax. By following, the SoftMax function was computedfor classification through equation 14,

$$R(j = c \backslash i) = \frac{e^{jc}}{\sum_{c=1}^{C} e^{jc}} \quad (14)$$

Let's assume, R is the probability, and C is the total amount of output class. This equation converts raw output scores into probabilities for each class. After converting raw output scores into probabilities for each class $\mathcal{L}$ Loss function was performed through equation 15,

$$\mathcal{L} = -\sum_{x=1}^{N} \sum_{c=1}^{C} j_{x,c} \log\left(R(j = c \backslash i_x)\right) \quad (15)$$

Let's assume $\mathcal{L}$ is the total loss of the dataset, N is the number of samples in the dataset and $j_{x,c}$ is the indicator of the true label. This equation measures the difference between predicted and actual labels, and it optimizes predictions by minimizing classification errors. After measuring the difference between predicted and actual labels, the u was updated through equation 16,

$$u \leftarrow u - \eta \frac{\partial \mathcal{L}}{\partial u} \tag{16}$$

In this equation let's assume, that u is the current weight, η is the learning rate, $\frac{\partial and\ \mathcal{L}}{\partial u}$ is the gradient of $\mathcal{L}$ with respect to u. This equation (Backpropagation) updates u to improve model accuracy during training. By successfully differentiating crucial characteristics such as building materials, structural designs, closeness to fault lines and seismic event size, the MLPL-NN ensures accurate damage classification.

3. Results and Discussion

The precision, recall, accuracy, F1 score, and time complexity are used to measure how well the introduced procedures are executed. Using the MLPNN methodology, this review finds accurate and dependable construction material detection for earthquake prevention using the current KNN, DCNN and GBR-XGB methodologies.

Table 1. Simulation Parameters

Parameters	Values
Name of the Dataset	Concrete Compressive Strength
No. of Records	1030
Language	Python
Tool	Anaconda

The simulation results and the parameters of this work are shown in Table 1. There are 1030 datasets in the Concrete Compressive Strength dataset, which is used to categorize the strength of concrete. The Anaconda tool and Python are used in the implementation process.

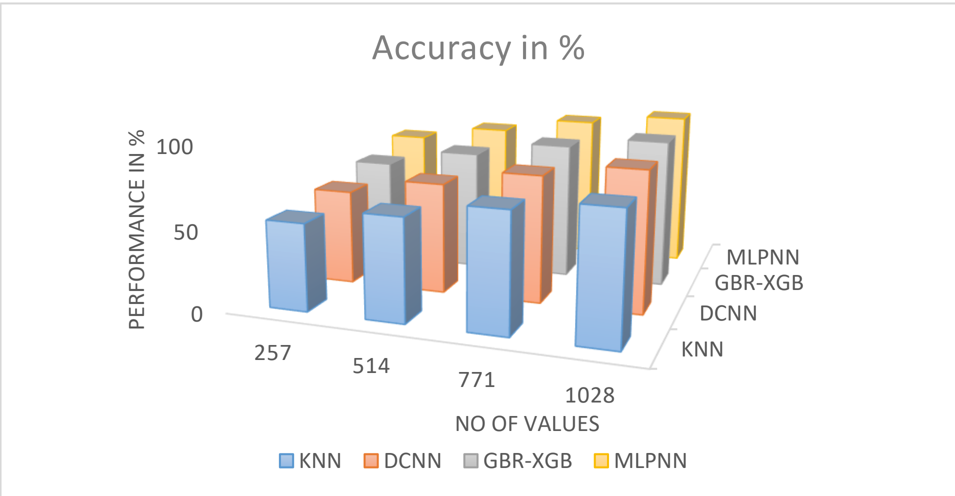

Fig 2. Accuracy performance in %

According to Figure 2, the accuracy performance of the MLPNN is 96.3%, the accuracy execution of the KNN is 78.94%, the accuracy of the DCNN is 86.4%, and the accuracy of the GBR-XGB is 91.2%. Compared to the other approaches, the MLPNN has achieved a high level of accuracy. In most circumstances, a high accuracy guarantees that the model forecasts the compressive strength values accurately.

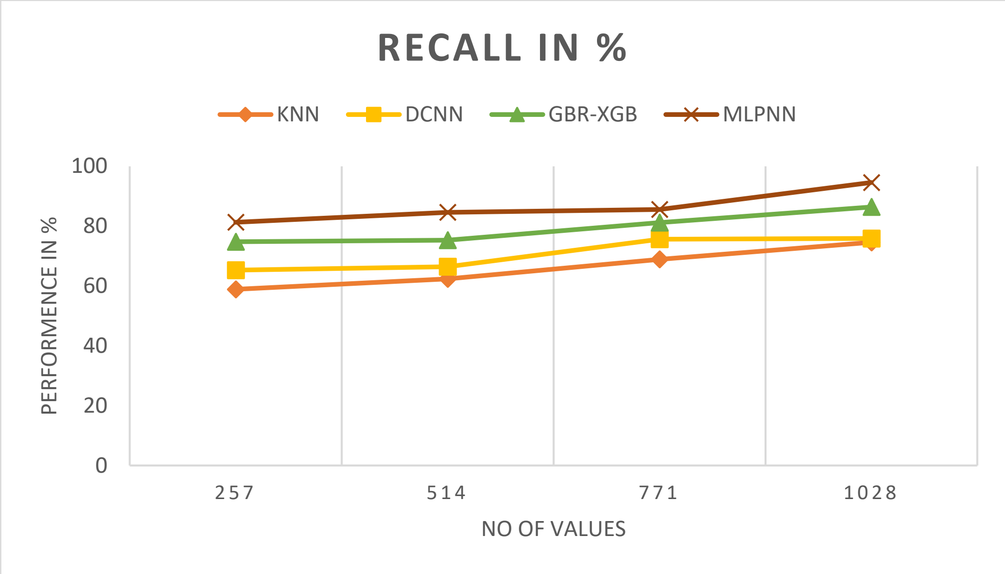

Fig 3. Recall performance in %

Figure 3 shows that the MLPNN's recall performance is 94.6%, the KNN's recall execution is 74.6%, the DCNN's is 75.9%, and the GBR-XGB's is 86.4%. Compared to the prior approach, the deployed methodology has a higher recall value. It makes sure that every instance of weak concrete is found, preventing possible structural problems.

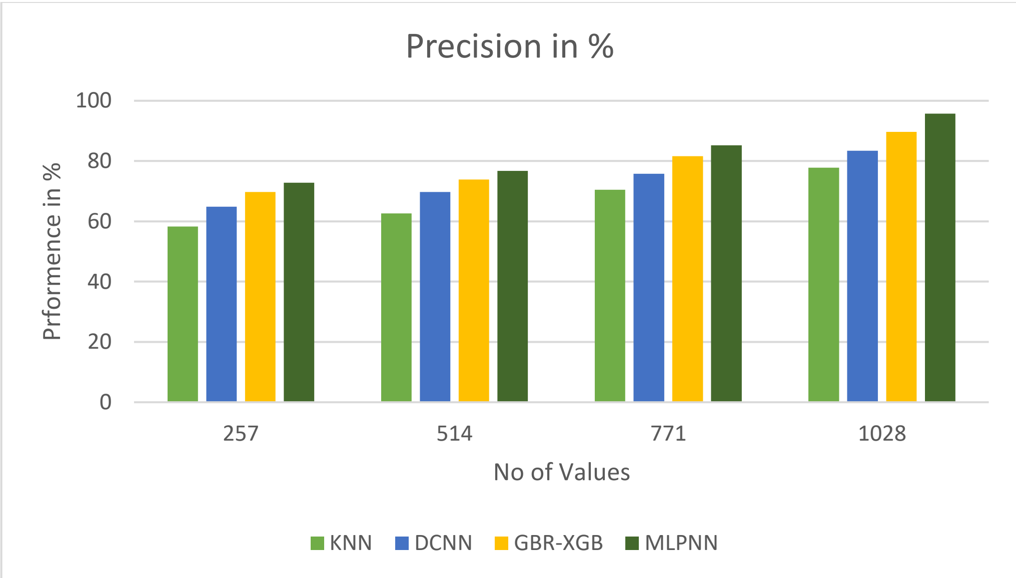

Fig 4. Precision performance in %

Figure 4 shows that the KNN's precision execution is 77.8%, the DCNN's is 83.4%, the GBR-XGB's is 89.7%, and the MLPNN's is 95.7%. Compared to the prior technique, the deployed methodology is more precise. There are fewer inaccurate predictions of high compressive strength when it is actually low when the precision value is high.

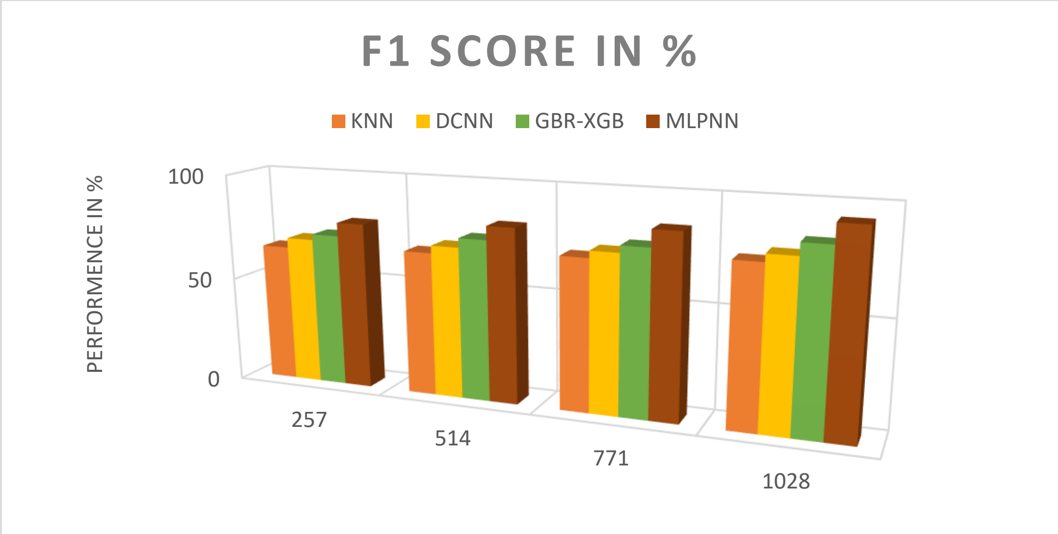

Fig 5. F1 score performance in %

Figure 5 shows that the KNN's F1 score execution is 75.3%, the DCNN's is 78.9%, the GBR-XGB's is 84.6%, and the MLPNN's is 93.6%. Compared to the prior technique, the deployed methodology has a higher F1 score. It gives an extensive overview of model performance by combining precision and recall, particularly in cases where the dataset contains unbalanced classes.

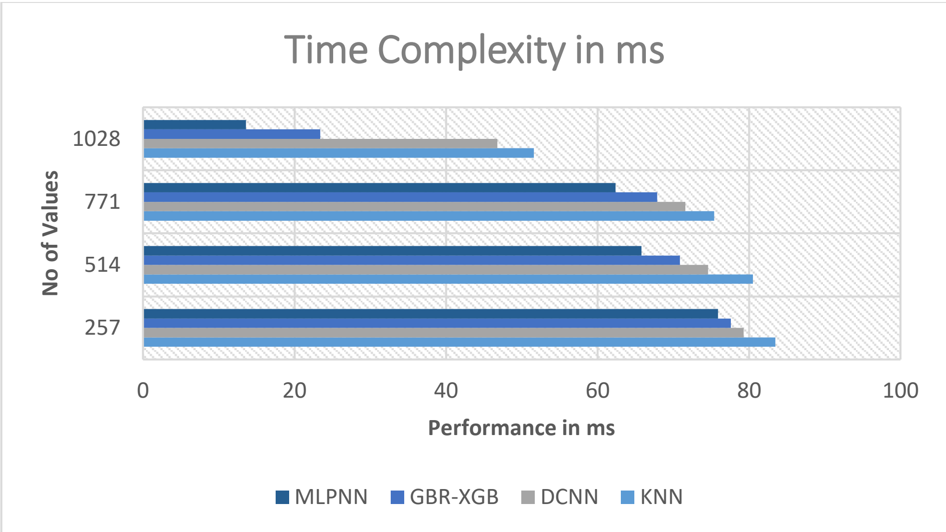

Fig 6. Time complexity performance analysis in %

Figure 6 shows that the KNN's time complexity performance is 51.6 ms, the DCNN's is 46.8 ms, the GBR-XGB's is 23.4 ms, and the MLPNN's is 13.6 ms. Compared to the prior technique, the deployed methodology has a far lower temporal complexity. Large datasets may be processed rapidly by a model with minimal time complexity, which makes it scalable for industrial applications.

4. Conclusion

In conclusion, the research highlighted the limitations of conventional concrete design parameters, which often fail to accommodate the necessary plasticity for earthquake resistance. It acknowledged the challenges associated with predicting the performance of concrete mixes, emphasizing the time and cost involved in extensive testing. By introducing the AI-based MLPNN method, the study presented a promising alternative that streamlines the design process for earthquake-resistant structures. Through the integration of CSN and the DFE-RN, essential features of concrete materials were effectively identified. The MLPNN method demonstrated significant improvements in classification accuracy and overall efficiency, reducing reliance on empirical testing. Ultimately, this research indicated the potential to transform the building industry by enabling the construction of concrete with enhanced properties, thereby expediting innovation and improving structural safety in the face of seismic challenges.

References

[1] Hu, Y., Wang, W., Li, L., & Wang, F. (2024). Applying Machine Learning to Earthquake Engineering: A Scientometric Analysis of World Research. Buildings, 14(5), 1393. https://doi.org/10.3390/buildings14051393

[2] Coskun, O., Aktepe, R., Aldemir, A., Yilmaz, A. E., Durmaz, M., Erkal, B. G., & Tunali, E. (2024). Seismic risk prioritization of masonry building stocks using machine learning. Earthquake Engineering & Structural Dynamics, 53(14), 4432-4450. https://doi.org/10.1002/eqe.4227

[3] Alipour, M., & Harris, D. K. (2020). Increasing the robustness of material-specific deep learning models for crack detection across different materials. Engineering Structures, 206, 110157. https://doi.org/10.1016/j.engstruct.2019.110157

[4] Mangalathu, S., Sun, H., Nweke, C. C., Yi, Z., & Burton, H. V. (2020). Classifying earthquake damage to buildings using machine learning. Earthquake Spectra. https://doi.org/10.1177/8755293019878137

[5] Ahmad, A., Ahmad, W., Aslam, F., & Joyklad, P. (2022). Compressive strength prediction of fly ash-based geopolymer concrete via advanced machine learning techniques. Case Studies in Construction Materials, 16, e00840. https://doi.org/10.1016/j.cscm.2021.e00840

[6] Hong, T., Wang, Z., Luo, X., & Zhang, W. (2020). State-of-the-art research and applications of machine learning in the building life cycle. Energy and Buildings, 212, 109831. https://doi.org/10.1016/j.enbuild.2020.109831

[7] Maltare, N. N., Sharma, D. & Patel, S. (2023). An Exploration and Prediction of Rainfall and Groundwater Level for the District of Banaskantha, Gujrat, India. International Journal of Environmental Sciences, 9(1), 1-17. https://www.theaspd.com/resources/v9-1-1-Nilesh%20N.%20Maltare.pdf

[8] Mangalathu, S., Jang, H., Hwang, S., & Jeon, J. (2020). Data-driven machine-learning-based seismic failure mode identification of reinforced concrete shear walls. Engineering Structures, 208, 110331. https://doi.org/10.1016/j.engstruct.2020.110331

[9] Yu, Y., Wang, C., Gu, X., & Li, J. (2018). A novel deep learning-based method for damage identification of smart building structures. Structural Health Monitoring. https://doi.org/10.1177/1475921718804132

[10] Kang, M., Yoo, D., & Gupta, R. (2021). Machine learning-based prediction for compressive and flexural strengths of steel fiber-reinforced concrete. Construction and Building Materials, 266, 121117. https://doi.org/10.1016/j.conbuildmat.2020.121117

[11] Feng, D., Liu, Z., Wang, X., Chen, Y., Chang, J., Wei, D., & Jiang, Z. (2020). Machine learning-based compressive strength prediction for concrete: An adaptive boosting approach. Construction and Building Materials, 230, 117000. https://doi.org/10.1016/j.conbuildmat.2019.117000

[12] Nguyen, H., Vu, T., Vo, T. P., & Thai, H. (2021). Efficient machine learning models for prediction of concrete strengths. Construction and Building Materials, 266, 120950. https://doi.org/10.1016/j.conbuildmat.2020.120950

[13] Han, T., Siddique, A., Khayat, K., Huang, J., & Kumar, A. (2020). An ensemble machine learning approach for prediction and optimization of modulus of elasticity of recycled aggregate concrete. Construction and Building Materials, 244, 118271. https://doi.org/10.1016/j.conbuildmat.2020.118271

[14] Asteris, P. G., Skentou, A. D., Bardhan, A., Samui, P., & Pilakoutas, K. (2021). Predicting concrete compressive strength using hybrid ensembling of surrogate machine learning models. Cement and Concrete Research, 145, 106449. https://doi.org/10.1016/j.cemconres.2021.106449

[15] Zhang, J., Huang, Y., Wang, Y., & Ma, G. (2020). Multi-objective optimization of concrete mixture proportions using machine learning and metaheuristic algorithms. Construction and Building Materials, 253, 119208. https://doi.org/10.1016/j.conbuildmat.2020.119208.

[16] Amador Terán Gilmore, Options for sustainable earthquake-resistant design of concrete and steel buildings, Earthquakes and Structures, Vol. 3, No. 6 (2012) 783-804.

[17] Mahipal Burdak, Earthquake Resistant Design & Construction Provisions for Reinforced Concrete Structure, International Journal of Science and Research (IJSR), Volume 7 Issue 9, September 2018, ISSN: 2319-7064

[18] Sanjivan Mahadik, S. R. Bhagat Earthquake Resisting Elements and Techniques in High Rise Buildings, International Journal of Innovative Technology and Exploring Engineering (IJITEE) ISSN: 2278-3075, Volume-9 Issue-3, January 2020.

[19] Durgesh C. Rai, Future trends in earthquake-resistant design of structures, Current science, vol. 79, no. 9, 10, 2000.

[20] Mohammad Shahjalal, Abul Kashem Mohammad Yahia, ASM Morshed, Nadia Islam Tanha, Earthquake-resistant building design: innovations and challenges, Global Mainstream Journal of Innovation, Engineering & Emerging Technology, Vol. 03, Issue 04, September 2024, Page:101-119.

[21] Behera, B., Datta, A.K. & Pal, A. Earthquake resistant design of framed reinforced concrete building using artificial intelligence model. Asian J Civ Eng 25, 4329–4342 (2024).

[22] Plevris, V. AI-DrivenInnovations in Earthquake Risk Mitigation: A Future-FocusedPerspective. Geosciences 2024,14, 244.

[23] Thomas Elliot, Hamed Kouchaki-Penchah, Victor Brial, Annie Levasseur, Sarah J. McLaren, Dynamic environmental payback of concrete due to carbonation over centuries, Sustainable Production and Consumption, Volume 51, 2024, Pages 236-247.

[24] Bing Xia, Jianzhuang Xiao, Shaofan Li, Sustainability-based reliability design for reuse of concrete components, Structural Safety, Volume 98, 2022, 102241, ISSN 0167-4730.

[25] Priyadarshani, Suchi & Rao, Roshan R & Mani, Monto. (2024). Paradigm Shifts in Building Construction Priorities in the Last Decade. Journal of the Indian Institute of Science. 10.1007/s41745-024-00437-5.

[26] Alessandra Mobili, Antonio Telesca, Milena Marroccoli, Francesca Tittarelli, Calcium sulfoaluminate and alkali-activated fly ash cement as alternative to Portland cement: a study on chemical, physical-mechanical, and durability properties of mortars with the same strength class, Construction and Building Materials, Volume 246, 2020, 118436, ISSN 0950-0618.

[27] Muhammad Nasir, Aziz Hasan Mahmood, Ashraf A. Bahraq, History, recent progress, and future challenges of alkali-activated binders – An overview, Construction and Building Materials, Volume 426, 2024, 136141, ISSN 0950-0618.

[28] Fadi Althoey, Wajahat Sammer Ansari, Muhammad Sufian, Ahmed Farouk Deifalla, Advancements in low-carbon concrete as a construction material for the sustainable built environment, Developments in the Built Environment, Volume 16, 2023, 100284, ISSN 2666-1659.

[29] Adeyemi Adesina, Recent advances in the concrete industry to reduce its carbon dioxide emissions, Environmental Challenges, Volume 1, 2020, 100004, ISSN 2667-0100.

[30] Nepomuceno Costa, Fernanda & Ribeiro, Daniel. (2020). Reduction in CO2 emissions during the production of cement, with partial replacement of traditional raw materials by civil construction waste (CCW). Journal of Cleaner Production. 276. 123302. 10.1016/j.jclepro.2020.123302.

[31] Wang, Z., & Cha, J. (2020). Unsupervised deep learning approach using a deep auto-encoder with a one-class support vector machine to detect damage. Structural Health Monitoring. https://doi.org/10.1177/1475921720934051