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ADVANCED PREDICTIVE MODELING FOR ENHANCING MANUFACTURING EFFICIENCY IN CONCRETE STRUCTURES: A NOVEL HYBRID APPROACH

Bichitra Singh Negi[1]
Akash Bhatt
Naveen Negi

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A B S T R A C T

Concrete structures are fundamental to modern infrastructure, and their efficient manufacturing is crucial for sustainable construction practices. However, traditional manufacturing processes often lack the precision and optimization required to meet evolving structural demands and sustainability goals. This deficiency becomes even more critical when considering seismic hazards, which pose a significant risk to the safety and resilience of urban infrastructure, particularly reinforced concrete buildings. Accurate assessment of seismic safety is crucial for effective risk mitigation and disaster preparedness. In this study, we introduce a novel approach that leverages a Fine-tuned Dragonfly Optimized Artificial Neural Network (FDO-ANN) to enhance the evaluation of seismic hazard safety in concrete Structures, utilizing data from the Structural Engineering Research Unit (SERU) database. Z-score normalization was employed as a data preprocessing approach to ensure the accuracy and reliability of the data utilized in the evaluation. Linear Discriminant Analysis (LDA) was used for feature extraction to identify essential characteristics or characteristics in reinforced concrete buildings that are associated with seismic safety. Python tool was used to analyze the proposed method. The proposed approach is assessed in terms of various parameters and compared to existing methods achieving an impressive accuracy of 95.6%. The proposed approach has the potential to inform more effective mitigation strategies, leading to increased resilience in the face of seismic hazards and improved protection of human lives and property.

1. INTRODUCTION

In an ever-evolving world, where urbanization continues to reshape our landscapes, the construction industry plays a pivotal role in shaping our cities and accommodating the growing global population. Reinforced concrete buildings are a tribute to human engineering prowess, providing architectural strength as well as versatility. They also face the difficult issue of surviving natural calamities, particularly seismic events,

[1] Corresponding author: Bichitra Singh Negi
Email: ce.bichitra@dbuu.ac.in

which can have disastrous implications (Gravett et al., (2021)). "Assessing the seismic hazard safety of reinforced concrete buildings" is critical because it protects not only the structural integrity of these structures but also the safety of those who live in them. There has been a paradigm change in the construction industry in recent years towards boosting industrial efficiency. This trend is being pushed by a variety of issues, including concerns about sustainability, economic considerations, and the need to fulfill ever-increasing needs for urban infrastructure (Athanasiou et al., (2020)). While increasing manufacturing efficiency is a desirable goal, it should not come at the expense of building safety, especially in seismically active areas. This paper investigates the critical confluence of production efficiency and seismic hazard safety assessment in reinforced concrete buildings. Earthquakes are a natural occurrence with unpredictable occurrences (Latif et al., (2022)).

When they strike, the forces they produce can exert enormous pressure on structures, resulting in structural failure and, in the worst circumstances, death. This inherent risk needs stringent safety precautions in building construction, particularly in areas with a history of seismic activity. Because of its strength and ductility, reinforced concrete has been a popular choice for building in such areas. However, the materials and methods utilized in reinforced concrete building construction are only one piece of the safety. Assessing seismic hazard safety entails determining a structure's ability to withstand ground vibrations caused by earthquakes. Engineers take into account the design of the structure, structural elements, foundation, and the local seismic hazard (Mangalathu et al., (2019)). This is a difficult procedure that necessitates a thorough understanding of both technical concepts and geological considerations. This assessment has traditionally been time-consuming and resource-intensive, frequently including extensive physical testing and simulations. Manufacturing efficiency in the construction sector refers to a variety of practices aimed at expediting the building process (Rahman et al., (2021)).

Prefabricated components, improved construction processes, and digital technologies are all examples of this. The goal is to shorten the construction process, eliminate waste, and maximize resource utilization. Such practices have several advantages, ranging from cheaper project costs to decreased environmental implications. The requirement to meet the expanding worldwide demand for infrastructure is one of the primary drivers of manufacturing efficiency in construction. Rapid urbanization, population expansion, and the demand for sustainable development have put enormous strain on the construction industry to deliver more, quickly (Zhang et al., (2023)). Furthermore, the building industry has been encouraged to embrace sustainability goals like lowering carbon emissions and resource use. These objectives have resulted in the creation of novel construction methods and materials. The drive for construction production efficiency is admirable, but it must be balanced with the vital necessity for seismic hazard safety (Fu et al., (2021)).

The problem is to balance these two goals while ensuring that efficiency benefits do not jeopardise the structural integrity of buildings in earthquake-prone areas. Using sophisticated materials and technical processes is one approach to reaching this equilibrium (Wakjira et al., (2021)). Researchers, for example, have been working on high-performance concrete mixtures that are not only stronger but also more durable and earthquake-resistant. These materials can improve the safety of reinforced concrete buildings without slowing down the construction process much (Kim et al., (2023)). Furthermore, the use of digital technology such as Building Information Modelling (BIM) and computer simulations has transformed building design and assessment. Engineers can use these technologies to forecast how a building will behave to seismic pressures with amazing accuracy. Engineers can optimize building designs for safety while maintaining manufacturing efficiency by modeling various situations (Zhao et al., (2020)). In this research, FTD-ANN (FDO-ANN) is proposed to enhance the evaluation of seismic hazard safety in concrete Structures.

- By leveraging FTD-ANN, which is a specialized neural network model, it aims to provide more accurate and reliable assessments of seismic risks.
- The proposed approach is designed to utilize data from the Structural Engineering Research Unit (SERU) database
- This research incorporates data preprocessing techniques, such as Z-score normalization and Linear Discriminant Analysis (LDA), to handle and extract relevant features from the data.

The remaining article is as structured follows: Section 2 outlines related work; Section 3 explains Materials and methods, Section 4 presents results and discussion, and Section 5 concludes and future research directions.

2. RELATED WORKS

ZhangNoureldin et al., (2022) introduced a novel approach that utilized machine learning techniques to address the seismic assessment and based on performance development of structures. The method predicted structural responses based on inputs like the period and strength ratio of the structure. The efficacy of the suggested technique was demonstrated through several applications in seismic design and evaluation. The results demonstrated that the new procedure was both dependable and precise, while also requiring significantly less computer resources compared to the conventional method. Harirchian et al., (2022) presented a practical framework, named the

"Improvement of Rapid Assessment of Earthquake Hazard Safety of Structures via Artificial Neural Networks (IRAEHSAN)", which utilized performance modifiers to enhance its effectiveness. The introduction of a Smartphone application prototype, based on the proposed strategy, presented a potentially valuable tool in the context of their increasingly digital society. It is important to note that the accuracy of their study was dependent upon several factors, including the selection of sample buildings, the methodologies employed for calculations, and the parameters utilized during the training and testing of the MLP model. Mangalathu et al., (2020) investigated the potential of ML and AI techniques for accurately identifying failure modes in concrete shear walls. A total of eight ML models were assessed to determine the optimal prediction model. Their article presented a suggested ML model based on the Random Forest approach, which was developed through a comprehensive evaluation process. They provided evidence that the failure mode of shear walls is influenced by various parameters.

Huang et al., (2019) investigated the utilization of a data-driven technique for the categorization of in-plane failure mechanisms of infill frames by the implementation of ML techniques. A total of six ML techniques were utilized and assessed to classify failure modes. The classification was based on nine structural factors that were applied as variables of input. The outcomes indicated that a majority of the models demonstrated a prediction accuracy rate of over 80%. Aladsani et al., (2022) presented a novel approach for predicting the drift capacity of unique structural walls. The proposed model utilized the extreme gradient boosting machine-learning technique and was developed using a comprehensive data set conducted on special boundary element walls. The efficacy of the suggested approach was assessed by a nested cross-validation procedure, which demonstrated its higher prediction abilities compared to the empirical solution utilized in ACI 318-19. To address the issue of limited understanding inherent in the model, the utilization of Shapley values could be employed. Additive explanations were employed to analyze the relative impacts of specific input factors and their interactions on the drift capacity. Fan et al., (2021) provided a comprehensive overview of the many uses of ML techniques in the domain of reinforced concrete bridges, encompassing the entire spectrum from design to inspection. Their finding illustrated the significant computational capacity and image processing proficiency of ML in addressing many facets of reinforced concrete bridges. The proposed method exhibited superior performance in comparison to conventional techniques for identifying structural damage and predicting strength, achieving near real-time capabilities. The utilization of ML for the prediction of concrete strength and bridge member performance had reached a considerable level of development, demonstrating a certain degree of maturity.

Işık et al., (2021) examined the seismic behavior of reinforced concrete structures based on variations in material strength and design spectra. A sample reinforced concrete building underwent structural analysis with the provided spectrum curves and material strengths. The phenomenon of increased rigidity in the structure was noted to correlate with the rise in concrete strength. They concluded that the utilization of site-specific design spectra, which were produced for various provinces, significantly impacted the calculated demand displacement values during analysis. They also investigated the material differentiation among the stories within the structure. Harirchian et al., (2020) examined the effectiveness of utilizing an ML application, specifically an SVM model, to predict damage and classify it accordingly. The utilization of their technique had the potential to facilitate strategic risk management decision-making and risk assessment for buildings susceptible to earthquakes in advance of such disasters. The findings revealed that the use of parameters yielded an accuracy rate of 52%, which could be considered satisfactory given the sample size employed. Mangalathu et al., (2019) presented an approach for efficiently assessing the damage state of bridges by leveraging the capabilities of ML algorithms. In contrast to the current techniques, the approach proposed the unique characteristics of bridges while evaluating their state of degradation. The methodology described in their study was illustrated by the application to two-span box-girder bridges located in California. They investigated the performance of different ML models. The analysis of ML models for different bridge designs revealed that the Random Forest (RF) model exhibited superior performance in comparison to alternative ML models.

Hamidia et al., (2022) presented a novel approach that utilized ML techniques to automate the diagnosis of damage states in non-ductile reinforced concrete moment frames (RCMFs). The proposed strategy used visual indices derived from crack patterns observed on the concrete surface. Several predictive models based on ML were developed to estimate the maximum drift ratio. These algorithms used the available information of the specimen to make accurate estimations. Won et al., (2021) presented a proposed framework for the development of an artificial neural network (ANN) model. The model aimed to forecast the seismic performance levels of building structures by considering the impacts of soil-structure interaction. The incorporation of the soil-structure relationship impact into the “single-degree-of-freedom model” was achieved by a 3-step investigation presented in their article. The framework that had been established and presented in their study allowed for the inclusion of soil–structure interaction (SSI) effects inside the model. Pham et al., (2020) presented an ML model that demonstrated efficacy in forecasting long-term deflections in reinforced concrete flexural members, specifically beams and slabs that had experienced cracking. Their study involved the evaluation of a prediction model's effectiveness by conducting a comparative analysis of its predicted accuracy. Their analysis included the examination of single and ensemble ML models, as well as empirical approaches. The evaluation was conducted using a substantial dataset of long-term testing conducted on RC flexural members.

Luo et al., (2018) introduced a new "machine learning–based backbone curve model (ML-BCV)" that offered a swift and accurate prediction of curves for columns that were susceptible to flexure and shear. The proposed model incorporated multioutput least-squares SVM to identify the relationship along both input/output variables. Additionally, "a grid search optimization technique" was included to enhance the efficiency of the training procedure. The experimental findings indicated that the proposed method exhibited more robustness and accuracy in comparison to conventional modeling methodologies. Ye et al., (2022) presented a conceptual framework for the expeditious evaluation of structural damage and condition assessment following earthquakes. The system incorporated satellite, "unmanned aerial vehicle (UAV), and Smartphone technology, together with a DL technique". UAVs and Smartphones could acquire visual representations of the structural elements of post-earthquake bridges. A novel approach was devised to assess the security level of risk of bridges after an earthquake.

3. MATERIALS AND METHODS

In this research, the FTD-ANN method is introduced to enhance the evaluation of seismic hazard safety in concrete Structures. To improve predictive accuracy, the data is normalized using Z-score normalization, LDA is used to extract characteristics, and Fine-tuned Dragonfly Optimization is used to select the best features. Figure 1 displays the flowchart of this research.

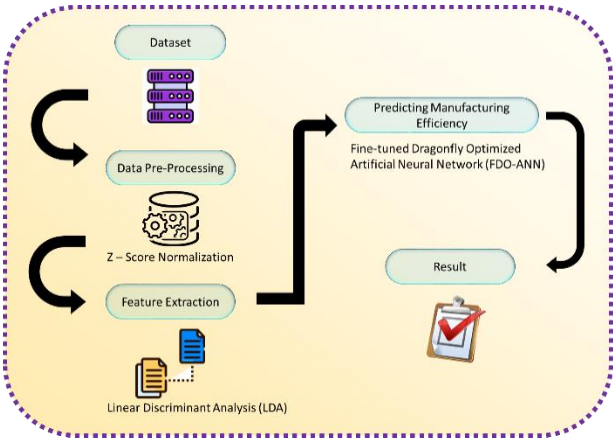

Figure 1. Flowchart of Manufacturing Efficiency in Concrete Structures

3.1 Dataset

The efficacy of the suggested methodology was assessed through an evaluation of the buildings. To accomplish the objective, a dataset consisting of "28 reinforced concrete buildings in Bingöl and 484 reinforced concrete buildings in Düzce was obtained from the SERU (Structural Engineering Research Unit) database”. This database was compiled through a survey conducted by a research group.

3.2 Data pre-processing

Cleaning, organizing, and manipulating raw data collected from various sources is a crucial part of data preparation for evaluating the seismic safety of concrete and its manufacturing. This stage makes sure that the information utilized in the analysis, including manufacturing data, is accurate and suitable for assessing the structural integrity of these buildings. The process involves sorting, arranging, and adjusting data from diverse origins, ensuring its quality and relevance for the evaluation of seismic risk in reinforced concrete buildings and manufacturing contexts. This meticulous data handling contributes to the overall reliability of the assessment and the manufacturing process. Here, the Z-score method has been chosen for the preprocessing.

The preprocessing step of normalization, which involves the deconstruction of data into its numeric properties, can be used to convert data values into a predefined range. As shown in Equation (1), Z-score normalization changes ana_u value from an attribute U to a' previously unknown range.

$$a' = \frac{a_u - m_u}{std(U)} \quad (1)$$

a'= Normalization result value

a_u=The attribute's value that needs to be normalized

b_u=Attribute for the mean value

$std(U)$=Standard deviation attributes U

3.3 Feature Extraction Using Linear Discriminant Analysis

The process of feature extraction involves identifying and isolating important characteristics or features from manufacturing efficiency data. This helps assess the structural capacity of manufacturing facilities to withstand seismic forces. Breaking down complex information into simpler components also enhances the evaluation of safety measures in manufacturing settings.

Finding a linear combination of features that effectively discriminates between two or more classes of objects is the goal of Fisher's linear discriminant analysis. The discriminant function is represented as

$$z = h(w) = x^S w \quad (2)$$

The vector of weights is denoted by x. The $D_j(j = 1,2)$ decision rule for a situation with two possible cases is as follows:

$$class(w) = \begin{cases} D_1, & if\ h(w) > 0 \\ D_2, & if\ h(w) < 0 \end{cases} \quad (3)$$

If $h(w) = 0$ is used, then w can go to either group. By optimizing a criterion function, we can obtain the x weight vector.

$$I(\mathrm{x}) = \frac{\mathrm{x^S T_A x}}{\mathrm{x^S T_x x}} \quad (4)$$

Where $T_A$represents the between-class scatter matrix and T_x represents the within-class scatter matrix. Case $D = [D_1, D_2, \dots\dots, D_5]$ for the full set of five is as follows. An alternative configuration for the five projection vector $x_j(j = 1,2, \dots\dots,5)isX = [x_1||x_2| \dots \dots |x_5]$. Then there's also:

$$D_j = h_j(w) = x_j^S w \Longrightarrow \mathrm{D} = \mathrm{X^S w} \quad (5)$$

The projection matrix x can be generated similarly to maximize a scalar objective function. There is no need for multivariate normality or homogeneity of variance to perform Fisher's linear discriminant analysis.

3.4 Fine-tuned dragonfly-optimized Artificial Neural Network (FDO-ANN)

Fine-Tuned Dragonfly Optimization

Selecting the most important features like material strength and design parameters to predict earthquake resistance in the analysis of concrete seismic performance is called feature selection. This makes the analysis simpler and improves the accuracy of seismic assessments for concrete buildings. Using dragonfly optimization is a good choice for feature selection when studying the seismic properties of concrete. Dragonfly optimization quickly identifies the most relevant features from a large pool of options. The most effective combination of features for evaluating seismic properties is determined through a simple trial and error process. This approach is useful in cases where many factors, such as manufacturing, need consideration when assessing concrete's seismic qualities.

The DA is inspired by dragonflies' distinct and intensified swarming behavior. DA swarms' behavior comprises both mobility and hunting. Assume there are M dragonflies in existence. Equation (6) gives the position of NDA.

$$a_o = \left(a_o^1, a_o^j, \dots, a_o^B\right) \quad (6)$$

The location of the o^{th} DA in the j^{th} searchable dimension is indicated byu_q^k, while the numbers i= 1,2,3, … . , B, and O denote the number of search agents.u_q^kdenotes the location of the oth DA in the j^{th} searchable dimension, whereas the digits i= 1,2,3, … . , B, and o^{th} denote the number of search agents.

The fitness function is approximated and generated randomly between the upper and lower bounds of parameters based on the initial location data. Equations (7) to (9) are used to “determine factors for updating dragonfly velocity and location”.

$$E_o = -\sum_{i=1}^{B} a - a_o \quad (7)$$

$$T_o = \frac{\sum_{i=1}^{B} N_g}{B} \quad (8)$$

$$X_o = \frac{i=1}{B} - a \quad (9)$$

The variables $E_o and\, A_o$ denote the velocity, and location of the o^{th} individual. S symbolizes a whole of people nearby, and E_o denotes the individual's current location. Equations (7) and (8) allow you to calculate P_o, which represents Attraction towards food, R_q, which “stands for Distraction from Opponents”.

$$Y_o = A^+ - A$$
$$P_o = A^- + A \quad (10)$$

A^-indicates the enemy source, A^+ indicates the food source, and U indicates the individual's current location. “We use the Euclidean distance” between each of the S dragonflies to calculate their distance from one another. Equation (10) determines the distance, denoted by v_{so}.

$$v_{so} = \sqrt{\sum_{i=1}^{j} (a_o, i - a_o, i)^2} \quad (11)$$

The DA's position will be updated using Equation (9) which is equivalent to the PSO location formulation. This will be done with Equation (8), which is similar to the PSO velocity formulation.

$$\Delta A_{d+1} = (uU_o + tT_o + lL_o + pP_o + yP_o) + z\Delta a_v \quad (12)$$

$$A_{d+1} = A_d + \Delta A_{d+1} \quad (13)$$

Chaotic patterns Initialization: The population diversity in a metaheuristic algorithm is significantly influenced by the initial location. The method's performance is ensured by a high-quality initial position. The dragonfly algorithm employs a random initialization process for the population in manufacturing. The positions created by the algorithm may tend to cluster either close to the best solution or at a considerable distance from it in manufacturing. This clustering behavior can potentially impede the search process for the optimal solution, leading to suboptimal outcomes in manufacturing. Chaos, being a multidimensional and intricate manifestation of a nonlinear system, exhibits distinct attributes such as randomness, ergodicity, and regularity in manufacturing. Hence, it is frequently employed in the initialization phase of meta-heuristic algorithms in manufacturing. Figure 2 shows the flow of Fine-tuned dragonfly optimization.

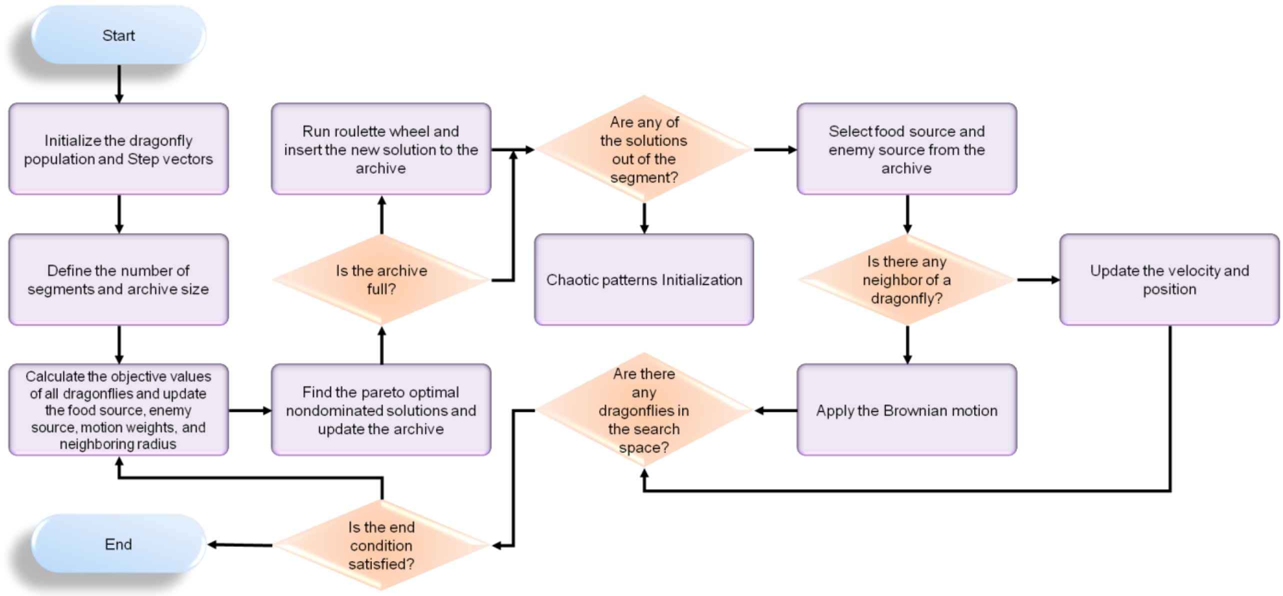

Figure 2. Flowchart Fine-tuned dragonfly optimization

The ergodic characteristic of the tent map exhibits superior characteristics. This implies that utilizing the tent map enables the attainment of a more homogeneous initial distribution inside the search area. Hence, the utilization of tent mapping was employed in this study to generate chaotic patterns for initialization,

$$w_{m+1} = \begin{cases} 2w_m & if\ w_m < 0.5 \\ 2(1-w_n) else\ w_m \geq 0.5 \end{cases} \quad (14)$$

The expression for converting the sequence into a tent-mapped search space is as follows:

$$W = Tent\ (M, dim).(va - ka) + ka \quad (15)$$

In this context, M represents the population size of dragonfly individuals, va *and* ka denote the upper and lower limits of the search space, and dim refers to the spatial dimension.

Artificial Neural Network (ANN)

The artificial neural network (ANN) architecture consists of several levels, including “the input layer, zero or more hidden layers, and the output layer”. The layers are connected by many nodes inside of every layer (Figure 3). The mathematical representation denoting the "value of neurons in the layer" immediately succeeding the input layer $w_i$is expressed as:

$$w_i = e(\overline{b_j}) = e(\textstyle\sum_i x_{ji} w_j - \bar{a}) \quad (16)$$

In the given context, it can be stated that j represents the layer immediately preceding the I layer. Similarly, i represents the layer immediately following the j layer. $w_j$denotes the input value in the neuron, while $e(\bullet)$ represents the “transfer or activation function”. The “weight coefficient x_{ji} signifies the degree of importance of the connection” among the neurons. The term $\sum_i x_{ji} w_j$ $\bar{a} =$ refers to the weighted summation and a denotes the “threshold or bias” value within the corresponding neuron.

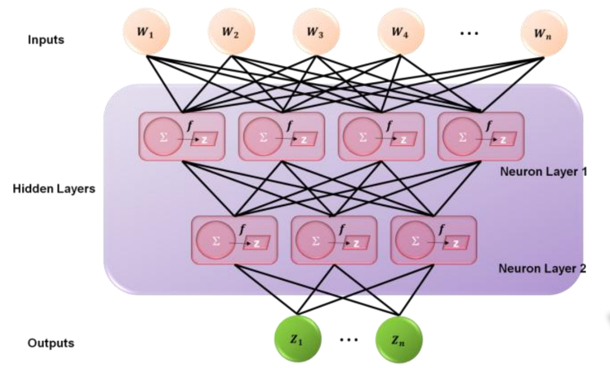

Figure 3. ANN structure

The neural network methodology utilizes a supervised procedure, wherein the model training incorporates known actual (target) outputs for the inputs and generates forecast values by comparing the objective and anticipated values. The algorithms, like "back-propagation, Quasi-Newton, and Levenberg-Marquardt algorithms", aim to minimize the differences between the forecasted values and desired values. The "weight and bias values" of the numerous "hidden and output layers" are determined through the utilization of learning techniques.

Artificial Neural Networks (ANNs) are widely used in assessing how concrete manufacturing structures behave during earthquakes. They are good at handling complex information and can give reliable predictions about how manufacturing buildings and other manufacturing structures will respond to seismic manufacturing forces. Using ANNs involves studying data about concrete manufacturing properties and seismic manufacturing forces. This helps manufacturing engineers make smart choices about how strong manufacturing concrete buildings and manufacturing infrastructure are. ANN plays a big role in making manufacturing concrete structures safer and more dependable, especially in places where manufacturing earthquakes are common.

The hybrid approach aims to provide a realistic and accessible method for assessing the seismic behavior of concrete. This goal is critical for maintaining the safety and resilience of these structures in earthquake-prone areas. This technology improves the accuracy of seismic evaluations by combining Fine-tuned dragonfly optimization with ANN, contributing to better design and construction methods for seismically exposed concrete structures. Algorithm 1 shows the pseudocode for FTD-ANN.

Algorithm 1: FTD-ANN pseudocode

import$dragonfly\_optimization$ as dfo
import$artificial\_neural\_network$ as ann
import$seismic\_data$ as data
def$objective\_function$(parameters):
$neural\_network =$ $ann.initialize\_neural\_network$(parameters)
$ann.train(neural\_network, data.training\_data)$
accuracy = $ann.evaluate(neural\_network, data.validation\_data)$
return -accuracy
optimizer = $dfo.initialize\_optimizer()$
$optimizer.set\_objective(objective\_function)$
$optimizer.set\_bounds(parameters\_bounds)$
$optimizer.set$_max_$iterations(max_iterations)$
$best\_parameters = optimizer.run()$
$best\_neural\_network$ = $ann.initialize\_neural\_network(best\_parameters)$
$ann.train(best\_neural\_network, data.all\_data)$
$seismic\_assessment$ = $ann.predict(best\_neural\_network, data.test\_data)$
print("Seismic Assessment Results:", $seismic\_assessment$)

4. RESULT AND DISCUSSION

In this section, we discuss the outcomes of the FDO-ANN approach for enhancing the evaluation of seismic hazard safety in concrete Structures. This FDO-ANN technique is designed and simulated using the Python tool (version 3.7), using 6GB of RAM and AMD Ryzen. The proposed method is analyzed in terms of various parameters, including Accuracy, recall, F1-score, MAE, MSE and RMSE and compared with existing methods such as decision tree (DT) (Asteris et al., (2022)), random forest (RF) (Asteris et al., (2022)), AdaBoost (Asteris et al., (2022)), Gradient Boosting Regressor (GBR) (Demertzis et al., (2022)), k-Nearest Neighbors Regressor (k-NNR) (Demertzis et al., (2022)) and Linear Regression (LR) (Demertzis et al., (2022)). Training and testing outcomes of (FDO-ANN) models are presented in Figure 4. A Confidence Interval (CI) is a statistical measure used in assessing the seismic efficiency of concrete manufacturing. It provides a range of values within which a parameter, like seismic strength, is likely to fall. This helps in gauging the reliability of concrete's seismic performance, aiding in safety assessments. Figure 5 displays the proposed FDO-ANN method's performance of CI.

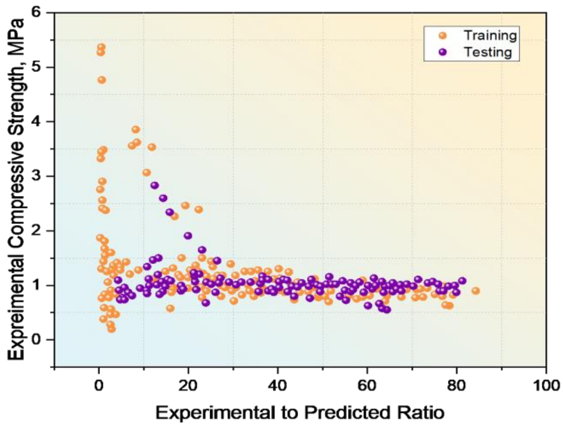

Figure 4. Predicted ratio of FDO-ANN in training and testing

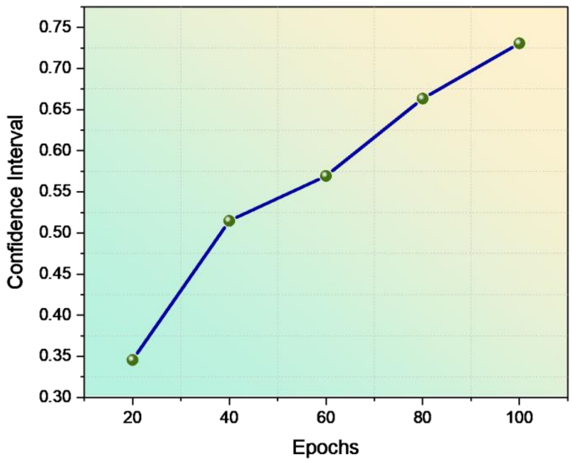

Figure 5. Confidence Interval (CI)

4.1 Accuracy

Accuracy metrics examine the accuracy of acquired data and forecasts while analyzing the seismic efficiency of concrete manufacturing. They assess how well the provided results correspond to the actual seismic performance of concrete structures. These indicators help ensure reliable assessments and inform manufacturing decision-making. The comparison of Accuracy is shown in Figure 6. Our suggested approach FDO-ANN has obtained 95.6% while existing DT, RF, and AdaBoost obtained 89.1%, 91.4%, and 93.1%. Our research findings indicate that our proposed approach achieves a significantly higher accuracy than the existing method.

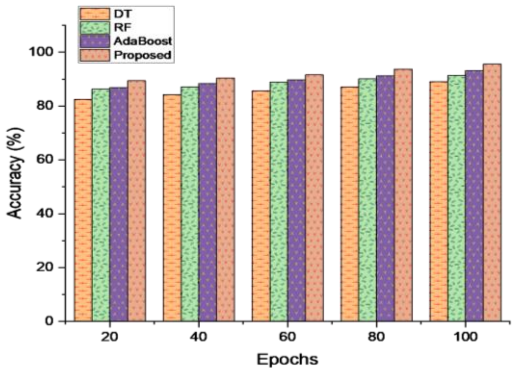

Figure 6. Accuracy

4.2 Recall

In assessing the seismic efficiency of concrete manufacturing, recall metrics involve examining the capacity to correctly identify concrete structures that are vulnerable to seismic waves. It assesses the fraction of genuine susceptible structures effectively discovered among all vulnerable structures. Figure 7 displays the recall comparison. Our proposed method, FDO-ANN, achieved a performance score of 96.8%, surpassing the existing techniques such as DT, RF, and AdaBoost, which scored 89.1%, 91.4%, and 93.1%, respectively. The results reveal that our new method has a significantly better recall compared to the existing approaches.

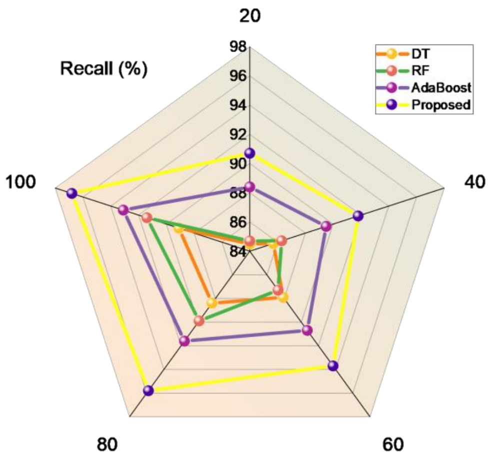

Figure 7. Recall

4.3 F1-score

The F1-score is a measure of the accuracy that seismic safety is assessed in concrete manufacturing efficiency. It provides a single statistic that combines accuracy (properly recognized safe structures) and recall (all safe structures identified). It aids in determining the appropriate balance between accurately detecting safe concrete constructions and eliminating false positives. The F1-score comparison can be found in Figure 8. FDO-ANN, the approach we recommend, achieved an impressive accuracy rate of 97.8%, outperforming the existing methods like DT, RF, and AdaBoost, which scored 89.5%, 91.5%, and 93.1%. The outcome demonstrates that the F1-score of our proposed approach is considerably higher than that of the existing method. The comparison between the existing and proposed approaches in terms of various parameters is presented in Table 1.

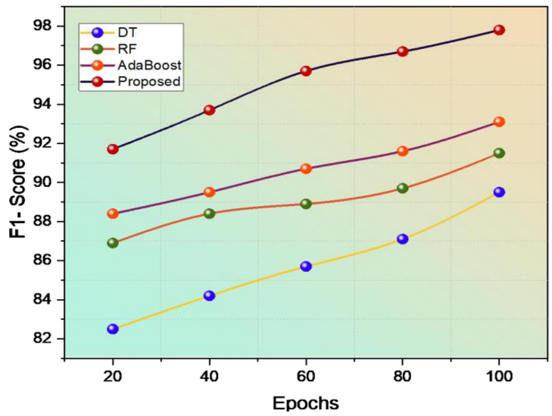

Figure 8. F1-score

Table 1. Outcomes of comparison

Methods	Performance Indicators		
	Accuracy (%)	Recall (%)	F1- score (%)
DT	89.1	89.1	89.5
RF	91.4	91.4	91.5
AdaBoost	93.1	93.1	93.1
Proposed	95.6	96.8	97.8

4.4 MAE

When evaluating seismic concrete manufacturing efficiency, the Mean Absolute Error (MAE) measures the average difference between anticipated and actual values. It quantifies how far the predictions differ from the true values, offering a simple measure of prediction accuracy. Figure 9 presents the MAE comparison. The results indicate that our suggested approach, FDO-ANN, has achieved 0.1087, while the existing methods DT, RF, and AdaBoost, only scored 0.1904, 0.3875, and 0.2757. The results reveal that the MAE of our proposed method is notably lower than that of the existing approaches.

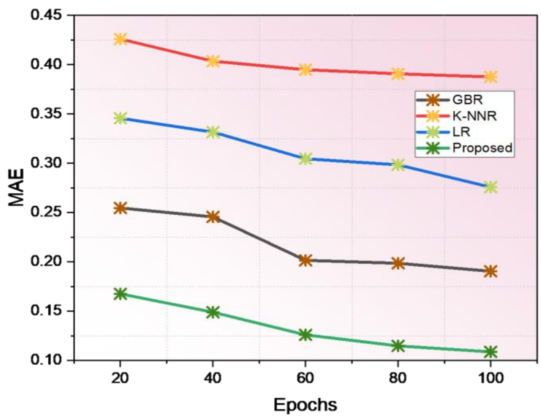

Figure 9. MAE

4.5 MSE

The Mean Squared Error (MSE) is a measure for analyzing the accuracy of seismic concrete manufacturing efficiency. The average of the squared deviations between forecasted and actual values is calculated. The MSE comparison is shown in Figure 10. Our proposed method FDO-ANN has obtained 0.0675, while current approaches such as DT, RF, and AdaBoost have obtained 0.0968, 0.1542, and 0.1585, respectively. Our suggested approach demonstrates a substantially increased MSE when contrasted with the existing method, as per the results.

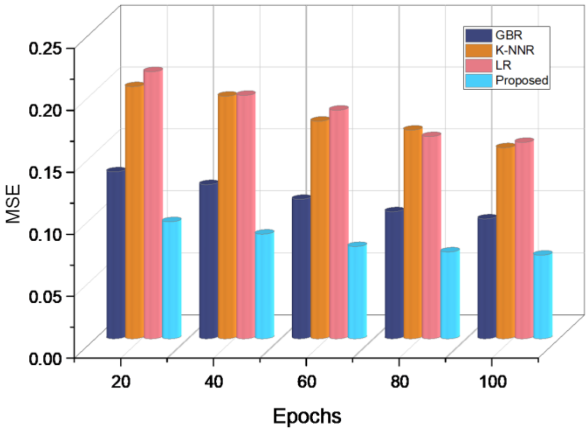

Figure 10. MSE

4.6 RMSE

The Root Mean Square Error (RMSE) is a metric used to analyze the accuracy of seismic production efficiency in concrete. It computes the average difference between expected and observed seismic data. Figure 11 provides the RMSE comparison. Comparatively, the performance of the existing approaches, DT, RF, and AdaBoost was 0.3068, 0.3875, and 0.3939, respectively; while our proposed approach FDO-ANN has 0.2875. The outcomes indicate that our proposed method has a much lower RMSE compared to the existing approach. Table 2 shows the Performance of the existing and proposed method.

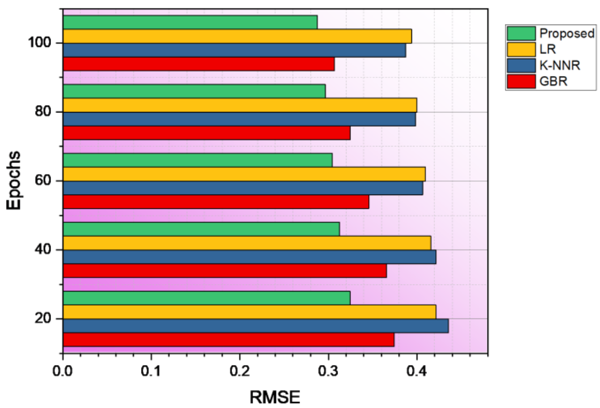

Figure 11. RMSE

Table 2. Performance metrics of the compared algorithms

Methods	Performance Indicators		
	MAE	MSE	RMSE
GBR	0.1904	0.0968	0.3068
k-NNR	0.3875	0.1542	0.3875
LR	0.2757	0.1585	0.3939
Proposed	0.1087	0.0675	0.2875

5. DISCUSSION

The proposed method addresses the limitations of various traditional machine learning such as decision tree (DT) (Asteris et al., (2022)), random forest (RF) (Asteris et al., (2022)), AdaBoost (Asteris et al., (2022)), Gradient Boosting Regressor (GBR) (Demertzis et al., (2022)), k-Nearest Neighbors Regressor (k-NNR) (Demertzis et al., (2022)) and Linear Regression (LR) (Demertzis et al., (2022)) algorithms for assessing seismic concrete buildings. To mitigate the limited accuracy of decision trees (DT) (Asteris et al., (2022)), the approach employs ensemble learning, combining multiple decision trees through boosting, which reduces overfitting while maintaining simplicity. For random forest (RF) (Asteris et al., (2022)), a novel feature selection technique is introduced to reduce complexity and prevent overfittings. To overcome the sensitivity of AdaBoost (Asteris et al., (2022)) to noisy data, robust preprocessing steps such as outlier detection and noise reduction are applied. Slow training in Gradient Boosting Regressor (GBR) (Demertzis et al., (2022)) is alleviated through hyperparameter optimization and parallel computing. The proposed method systematically determines the optimal number of nearest neighbors in the k-Nearest Neighbors Regressor (k-NNR) (Demertzis et al., (2022)) using cross-validation, enhancing model robustness. Lastly, to address Linear Regression (LR) (Demertzis et al., (2022)) linearity assumption, the approach incorporates polynomial terms to capture non-linear relationships. The proposed method utilizes ensemble learning, feature selection, preprocessing, optimization, and enhanced modeling to effectively mitigate the limitations of traditional algorithms, resulting in a more accurate and robust seismic concrete building assessment.

6. CONCLUSION

In today's rapidly evolving world, the construction industry is facing increasing demands for both efficiency and safety. As the global population continues to grow, urbanization is on the rise, leading to a surge in the construction of reinforced concrete buildings. These structures serve as the backbone of modern urban environments, providing shelter, workspaces, and infrastructure for millions of people. However, with the ever-present threat of seismic events, ensuring the safety and resilience of these buildings is of paramount importance. In this research, we developed a Fine-tuned Dragonfly Optimized Artificial

Neural Network (FDO-ANN) to enhance the evaluation of seismic hazard safety in concrete Structures. The proposed FDO-ANN model's performance was evaluated in terms of various parameters and compared with existing techniques. The proposed approach obtained accuracy (95.6%), recall (96.8%), F1-score (97.8%), MAE (0.1087), MSE (0.0675), and RMSE (0.2875). Developing and implementing predictive models can be time-consuming, and the study may not address the immediate needs of manufacturing processes that require quick decision-making. Future research could focus on the integration of real-time data streams into predictive models. This would enable manufacturing processes to make quick decisions based on up-to-the-minute information, reducing the lag time associated with traditional predictive modeling.

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Bichitra Singh Negi
Dev Bhoomi Uttarakhand University, Dehradun, India
ce.bichitra@dbuu.ac.in
ORCID 0000-0002-3142-0062

Akash Bhatt
Dev Bhoomi Uttarakhand University, Dehradun, India
Akashbhatt395@gmail.com
ORCID 0009-0009-9481-0621

Naveen Negi
Dev Bhoomi Uttarakhand University, Dehradun, India
Engineernaveen1009@gmail.com
ORCID 0009-0001-3642-0926