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Original Article

Intelligent Concrete Strength Classification Using Hybrid Neuro-Fuzzy Gradient Boosting and ANN Techniques

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Abstract - *The primary focus of this paper is to measure and classify the strength of the concrete with particular focus on the quality classification if 100% M-Sand is used in concrete instead of river sand with the addition of silica fume. Six different mixes of concrete were made by varying the proportion of cement with 0, 5, 10, 15, and 20% silica fume. It was found that the compressive strength of Mix-4 (with 10% silica fume) was 40.2MPa, which was 2% higher than that of conventional concrete and was 10.1% higher than that of the M-Sand mix. It was also noted that the split tensile strength and flexural strength increased by 15% and 14.9%, respectively. But all three properties went down 25% for a replacement of 20%. The quality classification of concrete was done using Hybrid Neuro Fuzzy Gradient Boosting, optimized using ASPO, and was compared with classical models. It was noted that the Hybrid Neuro Fuzzy Gradient Boosting model had a better accuracy rate than conventional models with an average accuracy of 97.2%, sensitivity ranging from 95.2% to 98.5%, Specificity ranging from 96.0% to 98.7%, and area under the receiver operating characteristic curve between 0.97 and 0.99. An Artificial Neural Network was also developed, and presented very high correlation coefficients (above 0.93), indicating a high potential application. From the observations, it was observed that the replacement of 10% silica fume with 100 % M-Sand showed high strength, which indicates high potential for its usage. It is also noticed that Hybrid Neuro Fuzzy Gradient Boosting has high potential for quality classification.*

Keywords - *Silica fume, M-Sand, Concrete strength classification, ANN, Quality assessment, Hybrid Neuro-Fuzzy Gradient Boosting.*

1. Introduction

While it is accepted that concrete forms the basis of modern civilization's infrastructure, its mechanical properties, such as compressive strength, splitting tensile strength, and flexural strength, have been seen to have a significant impact on it. One of the issues faced in dealing with concrete is that it is costly and time-consuming to attain its mechanical properties through standard laboratory testing procedures. In this regard, there is an increased interest in data-based Machine Learning (ML) techniques for reliable predictions or classifications of concrete quality and its mechanical properties based on various determinants of its quality. It has been seen in recent research that ML-based predictions have a high potential to reduce experimentation, enhance construction quality, and increase the overall efficiency of mixture design decisions in construction processes [1].

It is seen that there is an increased momentum for developing concrete classification models for predictions of quality or strength, rather than merely predictions of strength. It is seen that several recent research studies have extended ML predictions for compressive strength to cover tensile strength and flexural strength, thus demonstrating ML prediction generalizations for multiple concrete mechanical properties [2].

Within the last five years, various prominent research trends have been established. Gradient Boosting-based ensemble models such as XGBoost, LightGBM, and CatBoost have been effective in achieving high accuracy for strength prediction and classification problems due to their potential in learning complex relationships and robustness in dealing with heterogeneous data sets [3, 4]. Comparative analysis for benchmarking various implementations of Gradient boosting-based models has also proved their superiority in dealing with mix property prediction problems, such as quaternary mix and high-performance concretes, and have also proposed the importance of using interpretability techniques such as SHAP and feature importance for interpreting the results and relating them to mix design principles. Neuro-fuzzy inference models such as ANFIS have also been considered viable solutions if interpretability is a major issue for researchers, and hybrid models such as ANFIS-ANN have been effectively implemented for mix types such as high-strength and self-compacting concretes. Various recent studies have proposed the integration of Gradient boosting-based models with other optimizers and preprocessing techniques, such as Bayesian tuning and Optuna, for achieving high generalization potential for laboratory data sets [5].

Moreover, recent research has shown that there has been a shift towards hybrid and ensembling techniques, such as fuzzy, neural networks, and boosting, which can effectively strike a balance between accuracy, robustness, and interpretability, especially in mix types such as high-strength concrete, as shown in a recent research work where ANFIS, ANN, and statistical models were employed for quality prediction in high-strength concrete, which proved robust results in terms of predictive capabilities for neuro-fuzzy and ANN models [6]. Moreover, recent research has shown that there has been a shift towards boosting, such as gradient boosting, which has been proven to be superior in comparison to other machine learning techniques, especially in quality prediction and strength prediction in concrete, especially when optimized properly [7].

Keeping this in view, our research aims to employ a hybrid Neuro-Fuzzy + Gradient Boosting + ANN with an optimizer classification model, which can effectively predict and assess quality in terms of compressive, splitting tensile, and flexural strength [8].

1.1. Hybrid Neuro-Fuzzy–Enhanced Gradient Boosting

The main idea behind the proposed methodology is a hybrid approach combining fuzzy logic, neuro-fuzzy inference, and Gradient boosting classification. The use of a neuro-fuzzy system allows for incorporating domain knowledge (such as ranges for water-cement ratio, aggregate content, and curing age, etc.) in terms of fuzzy inference, thus allowing for uncertainty and non-linearity in input variables (such as those due to raw materials, etc.)[8]. Classical studies have proved that such a fuzzy-neural approach can be used to predict reasonable values for compressive strength in concrete with acceptable error margins.

In order to improve the accuracy and take into account complex, high-order interactions, the output from such a fuzzy approach (i.e., fuzzy features or neuro-fuzzy inference output) can be used to train a Gradient Boosting Classifier (GBC), which learns to classify discrete quality/strength levels for different mechanical properties such as compressive, tensile, and flexural strength [9].

Gradient boosting is a powerful approach to classification and regression problems, especially when dealing with intricate non-linear relationships and interactions among input features and data adaptability to different types of data distributions. Past research has proved that Gradient Boosting Regression (GBR), XGBoost, LightGBM, and CatBoost outperform regression-based and other machine learning approaches in predicting compressive strength in concrete, especially for complex and high-strength mixtures [10].

Furthermore, if a metaheuristic optimizer such as an adaptive swarm/particle swarm optimizer or other evolutionary algorithm is integrated to optimize hyperparameters for both neuro-fuzzy and Gradient boosting classifiers, such a hybrid approach has the potential to overcome problems such as overfitting, improve its ability to generalize from scarce experimental data, and perform reliably and with consistency in terms of classification accuracy for different mechanical properties [11].

Past research has proved that such optimized hybrid models to perform effectively in terms of predicting concrete strength. Thus, a hybrid neuro-fuzzy and Gradient boosting classifier approach has great potential for robust, accurate, and interpretable classification and quality prediction in concrete materials.

1.2. Artificial Neural Network-Based Prediction Models

Although the hybrid neuro-fuzzy boosting model was found to be efficient in prediction, the traditional ANN model was found to be the core model in the prediction of the properties of concrete mixes owing to the global function approximation ability, flexibility, and the potential to handle highly nonlinear relationships between the parameters, curing age, and admixtures, and the resultant mechanical properties [12]. In the last few years, ANN has been successfully applied by various researchers to the prediction of compressive strength, tensile strength, and flexural strength of various conventional and self-compacting mixes, including mixes with supplementary cementitious materials and industrial waste products.

ANN models have been found to be efficient in the prediction of compressive strength, split tensile strength, and flexural strength at various curing ages with satisfactory error rates, thus proving their global function approximation ability to handle the prediction of the mixes and the respective properties of interest. Moreover, in the comparative analysis, where ANN, ANFIS, and RSM models have been applied to the prediction of the properties of high-strength concretes, ANN models have been found to attain the highest correlation coefficient and the lowest prediction errors, thus proving its potential as an efficient model in the application of regression analysis with multiple variables and the potential to handle the complex nonlinear relationships between the variables [13].

However, ANN-based models have been found to have the lowest interpretability and are not applicable in classification without the application of further techniques [14]. However, the application of ANN as a hybrid model with rule-based classifiers might be more efficient in the prediction analysis [15].

1.3. Research Motivations and Scope of the Study

The objective of this work is the development, implementation, and validation of a system comprising neuro-fuzzy inference, meta-heuristic optimization, Gradient boosting classification, and ANN, aiming to evaluate and classify concrete quality in terms of its various mechanical properties, i.e., compressive strength, splitting tensile strength, and flexural strength. Contrary to most previous studies, instead of compressive strength, concrete quality will be classified in terms of other mechanical properties, i.e., splitting tensile strength and flexural strength, classified into discrete quality/strength categories relevant to concrete engineering applications, i.e., “low/medium/high," “reject/acceptable/high," etc.

The novelty in this work lies in the integration and implementation of fuzzy logic, neural networks, and the application of the ensemble method of the Gradient Boosting classification algorithm, along with the application of the optimization method, in the evaluation and classification of concrete quality in terms of its various mechanical properties. Although there has been extensive application of ML techniques in the prediction and evaluation of various mechanical properties of concrete, very few, if any, have attempted the integration and implementation of neuro-fuzzy, ANN, and the optimized version of the Gradient boosting classification algorithm, as has been attempted in this work, thus filling the gap between “black-box prediction” and “interpretable and engineering-relevant classification.”

2. Methodology

The methodology employed in this research provides a framework for strength-based quality classification of concrete using a hybrid neuro-fuzzy gradient boosting model, as shown in Figure 1 below.

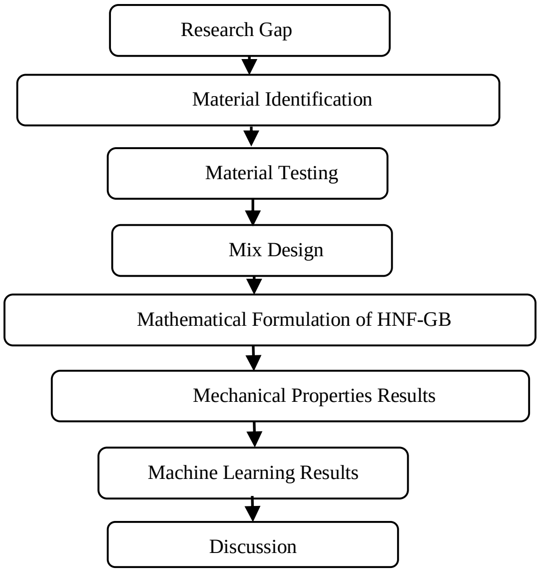


Fig. 1 Overall research methodology adopted in this study

The research begins with identifying a research gap, which results from the limitations associated with conventional destructive testing and conventional machine learning methodologies, thereby giving rise to a compelling research need for a reliable intelligence-based approach. The approach then involves material identification, where materials such as cement, fine aggregates, coarse aggregates, water, and cementitious materials are identified and verified against standard requirements. The approach then involves material testing, where physical properties are determined in order to allow controlled variations in design mixes corresponding to specified strength levels. After the concrete specimens are cast, they are tested to determine the compressive, split tensile, and flexural strengths, which are the values obtained from the mechanical property tests conducted on the concrete specimens. The data obtained from the mechanical property tests are the dataset used in the proposed classifier. The HNO-GB mathematical model combines the processes of generating the fuzzy membership, neuro-fuzzy adaptive learning, Gradient boosting, and classification, all of which are based on an optimization technique to improve the accuracy of the results obtained from the model. The model provides machine learning-based classifications of the quality of the concrete, which can be classified as low, medium, or high concrete strength, among other classifications. Finally, a detailed discussion is conducted to compare the performance of the experimental results obtained from the concrete specimens with the results obtained from the machine learning-based classifier model.

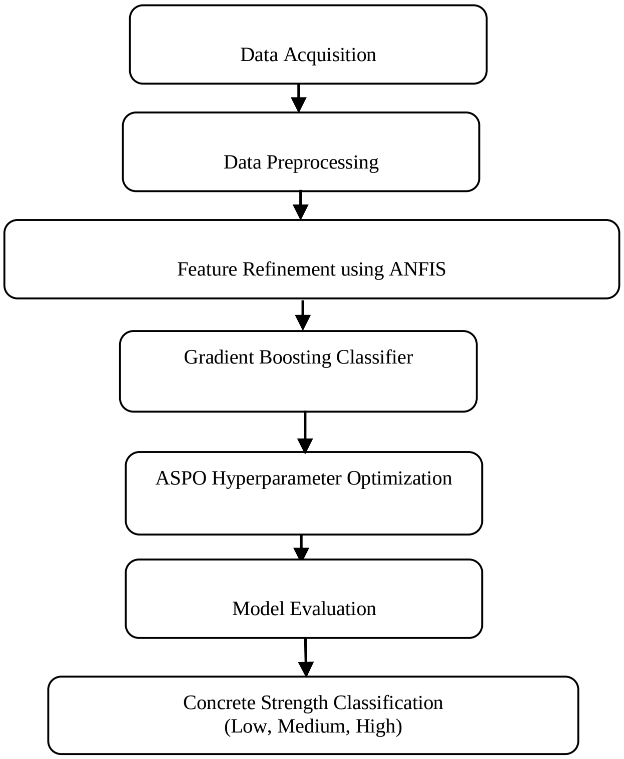


Fig. 2 Workflow of the Hybrid Neuro-Fuzzy Gradient Boosting (HNO-GB) model

The solution proposal offers an effective, definite, and strong model for classifying concrete compressive strength into specific strata, namely Low, Medium, and High. The synergistic framework is based on the integration of three state-of-the-art AI techniques, namely the Adaptive Neuro-Fuzzy Inference System for feature enhancement, the Gradient Boosting Classifier for an accurate multi-classification method, and the Adaptive Synergistic Parameter Optimization for hyperparameter optimization. The complete steps of the HNO-GB model are shown in Figure 2.

3. Framework for Concrete

The model consists of the following major components: (i) the materials and experimental testing phase, where the characterization of the constituent materials and the determination of the mechanical properties are considered; (ii) the mix-design methodology, through which concrete specimens are produced with distinct levels of concrete strength; (iii) the casting and curing phase; and (iv) the mathematical formulation of the HNO-GB model, where fuzzy inference, adaptive neuro-learning, and Gradient boosting classification are combined for the prediction of the quality of concrete.

3.1. Materials and Mechanical Testing Procedures

The type of concrete used for this study is based on Ordinary Portland Cement (OPC), ensuring the development of a strong and durable cement paste. Silica fume, a highly active pozzolanic material, is added to improve the densification of the structure and hence enhance the mechanical properties through secondary hydration. Manufactured Sand (M-Sand) is used as a 100% replacement for river sand, ensuring a sustainable alternative for the environment. River sand is used only to mention the properties of the materials. Crushed rock is used as a source for coarse aggregates to impart a structural base to the concrete for strength and stability. The use of silica fume and M-Sand results in an increased strength and quality of the concrete.

Table 1. Mechanical properties of cementitious material

Material	OPC 53 cement	Material	Silica Fume
Property	Measured value	Property	Measured value
Specific gravity	3.15	Specific gravity	2.2
Initial setting time	45 min	Bulk density (loose)	220 kg/m³
Final setting time	360 min	Residue on 45 µm sieve	< 5 %

The material characterization of OPC 53 grade cement and silica fume, as presented in Table 1, has a significant importance with regard to the suitability of materials in the production of concrete. As presented in Table 1, the specific gravity of the cement, which has a high value and is suitable for use in the production of a strong cement matrix in concrete, is 3.15. Furthermore, the initial and final setting times of 45 minutes and 360 minutes, respectively, are satisfactory and allow for a good amount of workability of the cement paste before the start of hardening. On the other hand, the specific gravity of silica fume, which is used as a mineral admixture in the production of concrete, has a value of 2.2, which is significantly lower than that of cement due to its ultrafine nature and a large percentage of amorphous silica content. Furthermore, the bulk density of this material, which is 220 kg/m³ in its loose condition, has a lightweight nature, thus allowing for an increased packing density of the material in a concrete structure. Additionally, the residue on 45 µm sieves, which has a value less than 5%, allows for its ultrafine nature and its ability to act as a pozzolanic material in the production of concrete.

Table 2. Mechanical properties of aggregates

Material	River Sand	Material	M-sand	Material	12 mm Aggregate
Property	Measured value	Property	Measured value	Property	Measured value
Specific gravity	2.65	Specific gravity	2.68	Specific gravity	2.7
Fineness modulus	2.85	Fineness modulus	3	Loose bulk density	1,500 kg/m³
Water absorption	1.20%	Water absorption	1.50%	Water absorption	0.80%

The physical properties of river sand, M sand, and 12 mm coarse aggregates are important for providing input values for mix proportioning and for determining the properties of the mix, as shown in Table 2. The specific gravity of river sand, 2.65, indicates its mineral composition, while its fineness modulus, 2.85, indicates its composition, maintaining a proper level of workability. The water absorption capacity of 1.20% indicates a proper level of porosity and moisture interaction during mixing. On the other hand, M sand has a higher value of specific gravity, 2.68, and a fineness modulus, 3.0, indicating coarser and more angular characteristics, while its water absorption capacity, 1.50%, indicates a higher level of roughness, requiring moisture adjustments during mixing.

The physical properties of 12 mm aggregates, which are crushed, indicate a higher value of specific gravity, 2.70, and a lower water absorption capacity, 0.80%, implying a higher level of density and durability, thereby contributing to a higher load-bearing capacity and lower porosity in the mix, and a loose bulk density of 1500 kg/m³, confirming its suitability for forming the main framework of the mix.

3.2. Concrete Mix Design Details

The mix design adopted for the present investigation was developed to evaluate the effect of silica fume addition on the mechanical performance and quality classification of concrete. In total, six mix proportions are adopted. Mix-1 represents the conventional control mix using river sand as the source material for the fine aggregate. In the case of Mixes 2 to 6, 100% M-Sand is adopted as an alternative source material to replace river sand, and silica fume is adopted as an alternative source material to replace the cement content using incremental weight percentages ranging from 0%, 5%, 10%, 15%, and 20% replacement by the weight of the cement content. The proposed mix design enables the evaluation of the combined effect of M-Sand and silica fume addition on the mechanical performance of concrete. The mix is designed using constant coarse aggregate, water content, and total binder content.

Table 3. Different mix proportions

ID	Cement (kg)	Silica fume (kg)	River sand (kg)	M-sand (kg)	12 mm aggregate (kg)	Water (lit)
Mix-1	380	0	728	0	1117	169
Mix-2	380	0	0	728	1117	169
Mix-3	361	19	0	728	1117	169
Mix-4	342	38	0	728	1117	169
Mix-5	323	57	0	728	1117	169
Mix-6	304	76	0	728	1117	169

Table 3 shows the detailed mix proportions adopted in this study. Mix-1 uses 380 kg of cement and river sand without silica fume, which will be considered a standard reference. Mix-2 will use the same amount of cement, replacing river sand completely with M-Sand. Mix-3, Mix-4, Mix-5, and Mix-6 will use silica fume in replacement of cement, i.e., 19 kg (5%), 38 kg (10%), 57 kg (15%), and 76 kg (20%), respectively, maintaining a constant cement content of 380 kg. The constant amount of coarse aggregate (1117 kg) and water content (169 L) will be maintained in all mixes, keeping workability constant. These proportions will help in understanding the performance improvement that can be obtained by incorporating silica fume into M-Sand concrete.

3.3. Specimen Preparation and Curing Regimen

For the purpose of this study, concrete specimens of varying sizes were prepared to study the properties at different curing ages. These specimens include cubes, cylinders, and prisms, each having specific testing criteria. Cube specimens of size 100 x 100 x 100 mm were prepared to study the compressive strength of concrete, as shown in Figure 3. Cylinders of diameter 100 mm and height 200 mm were prepared to study the split tension strength. Prism specimens of size 100 x 100 x 500 mm were also prepared to study the flexural strength.

All the materials were mixed well to obtain a good concrete mix. Then, each of the concrete specimens was poured into the respective moulds in layers. Each layer was compacted using a table vibrator to remove air bubbles and to properly densify the concrete. After pouring the concrete, the moulds were kept undisturbed at room temperature for 24 hours to allow initial setting. Then, all the specimens were immersed in potable water at ambient temperature in a curing tank. The curing ages used for this study are 7 days and 28 days, as shown in Figure 4.

After completing the curing period, the specimens were removed from the tank and tested to study the respective strength properties according to the IS codes.

Fig. 3 Casting of concrete specimens for mechanical testing

Fig. 4 Water curing of test specimens up to 28 days

3.4. Mathematical Formulation of the HNO-GB Model

Building upon the description of the methodological pipeline is discussed below, it is essential to provide a formal mathematical characterization of the ASPO-optimized Hybrid Neuro-Fuzzy Gradient Boosting (HNO-GB) framework. This subsection establishes the underlying mathematical structures of each component, showing how fuzzy inference, boosting, and evolutionary optimization work synergistically.

3.4.1. Neuro-Fuzzy Feature Optimization Layer

Let the dataset be represented as:

$$D = \{(x_i, y_i)\}_{i = 1}^N \tag{1}$$

Where $x_i = [x_{i1}, x_{i2} ... x_{id}]$ is the d-dimensional feature vector (cement content, water/cement ratio, curing days, aggregates, additives, etc.) and $y_i \in \{1,2,3\}$ represents the strength class (Low, Medium, High) [16].

The fuzzy rule base is defined as:

$$R_j : IF\ x_1\ is\ A_{1j} \wedge x_2\ is\ A_{2j} \wedge \cdots \wedge x_d\ is\ A_{dj}\ THEN\ f_j(x) = p_{0j} + \Sigma_{m = 1}^d\, p_{mj} x_m \tag{2}$$

- A_{mj}: fuzzy set defined by membership function $\mu_{A_{mj}}(x_m)$.
- p_{mj}: linear parameters optimized via hybrid learning.
- $f_j(x)$: linear consequent function.

The firing strength of rule R_j is:

$$w_j(x) = \prod_{m = 1}^d \mu_{A_{mj}}(x_m) \tag{3}$$

And the aggregated fuzzy output becomes:

$$y_{fuzzy}(x) = \Sigma_{j = 1}^M\, w_j(x)\, f_j(x) \,/\, \Sigma_{j = 1}^M\, w_j(x) \tag{4}$$

This refined feature y_{fuzzy} is concatenated with the original dataset to yield:

$$X' = [X, y_{fuzzy}] \tag{5}$$

3.4.2. Gradient Boosting Classification Layer

For classification into strength classes {C1, C2, C3}, the Gradient boosting classifier constructs an additive model [17]:

$$FT(x) = \Sigma_{t = 1}^T\, \eta \cdot h_t(x) \tag{6}$$

where:

- $h_t(x)$ = decision tree at iteration t.
- η = learning rate.
- T = number of boosting rounds.

The model minimizes the multiclass cross-entropy loss:

$$L = -(1/N)\, \Sigma_{i = 1}^N\, \Sigma_{k = 1}^3\, 1(y_i = k)\, log(\hat{p}_{ik}) \tag{7}$$

The gradient boosting process ensures misclassified samples receive higher weights in subsequent trees, thereby refining classification boundaries for concrete strength classes.

3.4.3. Adaptive Synergistic Parameter Optimization (ASPO)

Hyperparameter tuning is modeled as an optimization problem [18]:

$$\theta * = arg\ max_{\theta \in \Theta}\, Acc(X', Y;\ \theta) \tag{8}$$

where $\theta = [\eta, d_{max}, T, \sigma_\mu]$ are model hyper parameters and Acc(·) is classification accuracy.
ASPO employs Differential Evolution (DE):

Mutation

$$v_i(g + 1) = x_{r1}(g) + F \cdot (x_{r2}(g) - x_{r3}(g)) \tag{9}$$

Crossover

$$u_{ij}(g + 1) = v_{ij}(g + 1), if\ rand_j \le CR \tag{10}$$

$$u_{ij}(g + 1) = x_{ij}(g), otherwise$$

Selection

$$x_i(g + 1) = u_i(g + 1), if\ f(u_i(g + 1)) \ge f(x_i(g)) \tag{11}$$

$$x_i(g + 1) = x_i(g), otherwise$$

Where f (·) is the fitness function (classification accuracy). This process balances exploration (global search) and exploitation (local refinement), avoiding overfitting and ensuring optimal hyperparameters.

4. Result and Discussion

An analysis of the mechanical strength of the concrete specimens was performed after curing for 7 and 28 days. Experiments were performed to evaluate the compressive strength, split tension, and flexural strength of the concrete mix. Besides experiments, machine learning models were also used to perform predictions.

A Hybrid Neuro Fuzzy Gradient Boosting model was also developed to improve the prediction accuracy. An Artificial Neural Network was also used to evaluate the prediction. The results provide an in-depth analysis of the physical properties.

4.1. Compressive Strength Evaluation

The compressive strength is considered a key parameter for quality evaluation and classification of concrete, and this parameter has been adopted in this research for quality evaluation and classification of concrete.

Since the research aims to improve the performance of concrete using silica fume and 100% M-Sand, compressive strength serves as a conclusive parameter for assessing the improvement in concrete performance.

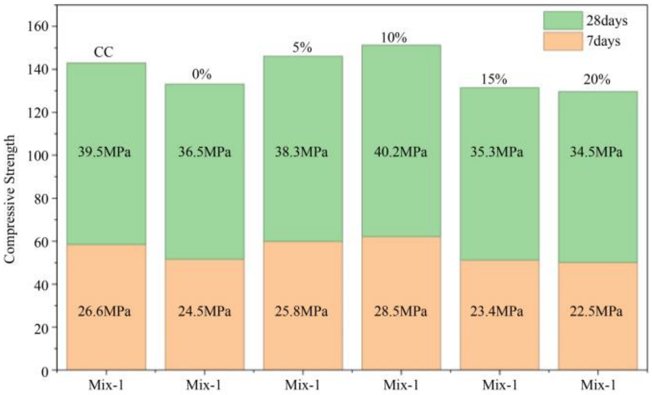


Fig. 5 7-day and 28-day compressive strength results for different concrete mixes

From the results obtained for the compressive strength tests, as shown in Figure 5, it is clear that with the addition of silica fume, the compressive strength is improved compared to the conventional concrete. The conventional concrete, Mix-1, showed a compressive strength of 26.6 MPa at 7 days and 39.5 MPa at 28 days. When natural sand is replaced completely with M-Sand without the addition of silica fume, Mix-2 showed a reduction in compressive strength to 24.5 MPa at 7 days and 36.5 MPa at 28 days. This indicates that M-Sand also needs to have a higher level of binder reactivity to produce high compressive strength. With the addition of silica fume, the developed concretes showed an improvement in compressive strength compared to Mix-2, as shown in Figure 5. This is due to the better pozzolanic reaction of silica fume. Mix-3 showed a compressive strength of 25.8 MPa at 7 days and 38.3 MPa at 28 days with 5% replacement of M-Sand with silica fume. Mix-4 showed the maximum compressive strength values of 28.5 MPa at 7 days and 40.2 MPa at 28 days, an improvement of 2% compared to the conventional concrete at 28 days. Mix-5 and Mix-6 showed a reduction to 23.4 MPa and 35.3 MPa at 28 days with 15% and 20% replacement levels, respectively. Mix-6 showed a reduction to 22.5 MPa and 34.5 MPa at 28 days. From the results, it is clear that 10% replacement of M-Sand with silica fume is the optimum level to produce high compressive strength for the developed concretes.

4.2. Split Tensile Strength Evaluation

The evaluation of the split tensile strength is significant in this research, as concrete is weak in tension. The addition of silica fume along with 100% M-Sand is expected to increase the tensile strength and the capacity to control cracks. The main aim of this research is to evaluate the effect of the replacement percentage on the bonding efficiency between the cement paste and the aggregate. The evaluation of this parameter is significant in validating the potential of the modified mix to enhance the resistance to the formation and propagation of cracks, thereby increasing the tensile strength and durability, hence the quality.

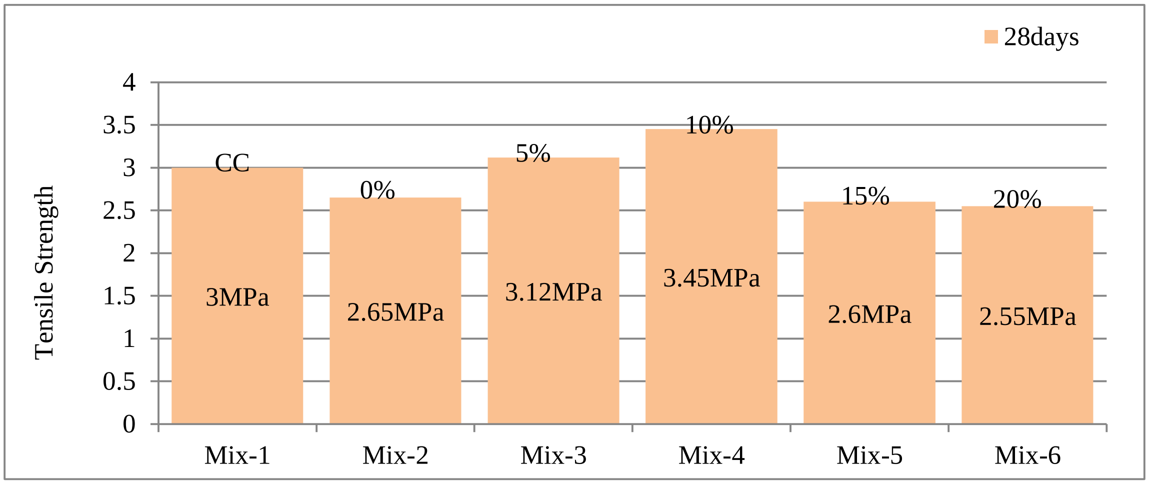


Fig. 6 Split tensile strength variations across concrete mix combinations

Split tensile strength test results presented indicate that the results vary with the amount of silica fume, as seen in Figure 6. Conventional concrete mix (Mix-1) has a split tensile strength of 3.0 MPa, which is the benchmark value. When the silica fume content is 0%, i.e., 100% M-Sand is used in the concrete mix (Mix-2), the split tensile strength slightly reduces to 2.65 MPa, indicating that M-Sand is not sufficient to completely replace natural sand in concrete mixes. As can be seen in Figure 6, the values of the split tensile strength for the mixes with silica fume at 5% and 10% are 3.12 MPa and 3.45 MPa, respectively, which is a 4% and 15% improvement, respectively, than the values obtained in the conventional concrete mixes. The split tensile strength decreases to 2.60 MPa and 2.55 MPa, respectively, in the mixes with silica fume content of 15% and 20% in the concrete mixes (Mix-5 and Mix-6), respectively, which can be explained by the excess amount of silica fume in these mixes and may require further water addition, resulting in the imbalance in these mixes. Hence, the optimal.

4.3. Flexural Strength Evaluation

Flexural strength is considered crucial in this study, as it examines how silica fume and 100% M-Sand affect the tensile strength of concrete under flexural conditions. The research, in particular, targets improving mechanical properties through sustainable replacement materials, and thus, flexural strength becomes a crucial factor in examining how concrete will perform under crack resistance and loading capacity. By examining the variation in flexural strength under various replacement ratios of silica fume, this study identifies the optimal replacement ratio that enhances concrete densification, bonding, and durability.

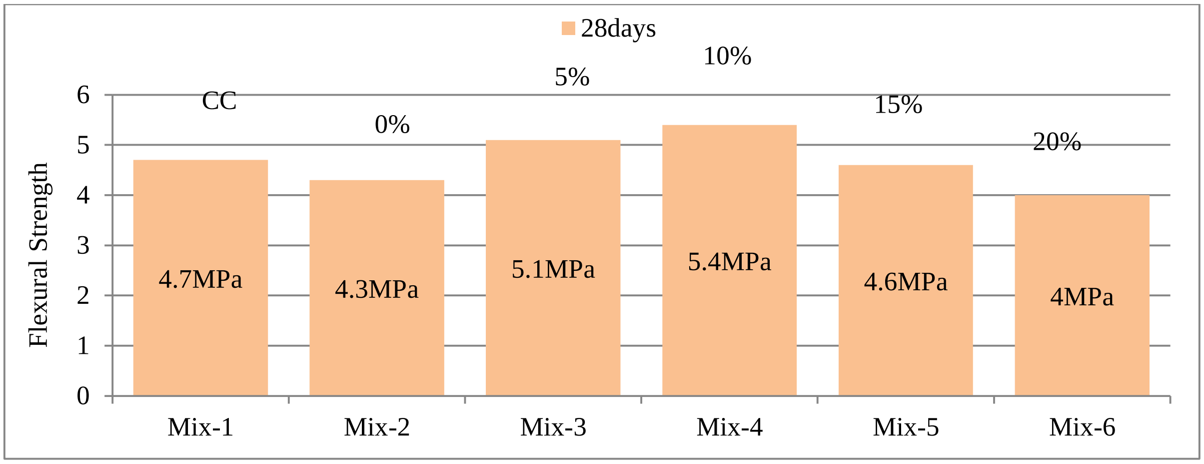


Fig. 7 Flexural performance of concrete under varying mix compositions

The results obtained from the flexural strength tests performed on the concrete mixes after 28 days, as depicted in the above graph, show the effect of the silica fume replacement content on the performance of concrete mixes prepared using 100% M-Sand, as depicted in Figure 7. In the conventional concrete mix (Mix-1), the flexural strength obtained is 4.7 MPa. In the concrete mixes prepared using only M-Sand in the absence of silica fume (Mix-2), the flexural strength obtained is slightly lower, i.e., 4.3 MPa, which is a reduction of 8.5% compared to the conventional concrete mixes, due to the absence of micro-fillers in the M-Sand mixes. In the concrete mixes prepared using 5% silica fume as a replacement content in M-Sand (Mix-3), the flexural strength obtained is 5.1 MPa, which is an improvement of 8.5% compared to the conventional concrete mixes, and an improvement of 18.6% compared to the M-Sand mixes, due to the addition of silica fume, which provides better densification in the matrix. In the concrete mixes prepared using 10% silica fume as a replacement content in M-Sand (Mix-4), the maximum flexural strength obtained is 5.4 MPa, which is an improvement of 14.9% compared to the conventional concrete mixes and an improvement of 25.6% compared to the M-Sand mixes, due to the addition of silica fume, which provides better densification in the matrix. In the concrete mixes prepared using 15% silica fume as a replacement content in M-Sand (Mix-5), the flexural strength obtained is 4.6 MPa, which is a reduction of 14.8% compared to the maximum flexural strength obtained in the concrete mixes prepared using 10% silica fume, but close to the flexural strength obtained in the conventional concrete mixes. In the concrete mixes prepared using 20% silica fume as a replacement content in M-Sand (Mix-6), the flexural strength obtained is 4.0 MPa, which is a reduction of 25.9% compared to the maximum flexural strength obtained in the concrete mixes prepared using 10% silica fume, due to the excessive amount.

4.4. Hybrid Neuro-Fuzzy Gradient Boosting Performance Assessment

This section presents the empirical validation of the Hybrid Neuro-Fuzzy Gradient Boosting (HNF-GB) model developed in Section 3, with optimization performed using the Adaptive Sandpiper Optimization (ASPO) algorithm. The performance of the proposed model is evaluated through a comparative analysis with four widely used machine learning models, namely Random Forest (RF), Support Vector Machine (SVM), Convolutional Neural Network (CNN), and Decision Tree (DT). The effectiveness of each model is assessed using standard classification performance metrics. Furthermore, the obtained results are interpreted in the context of structural engineering applications, emphasizing their significance for structural safety assessment, quality control, and reliable decision-making in construction practices.

4.4.1. Dataset Allocation and Stratified Sampling

It was based on the data set consisting of 1,005 concrete samples, categorized into three classes according to the performance of the concrete's strength, namely Low (196 samples), Medium (449 samples), and High (360 samples). The data set, as presented in Figure 8, shows an outstanding imbalance in the classes, with the medium class being the most predominant [20].

In order to avoid bias while training the model, stratified sampling was performed, ensuring an equal proportion in the representation of the classes in the 70% Training Set and the 30% Test Set, as presented in Figure 9. The basis of the stratification is to ensure that there is a valid and fair evaluation of the generalization ability of the classifier over all the grades of the strength that the model is expected to perform.

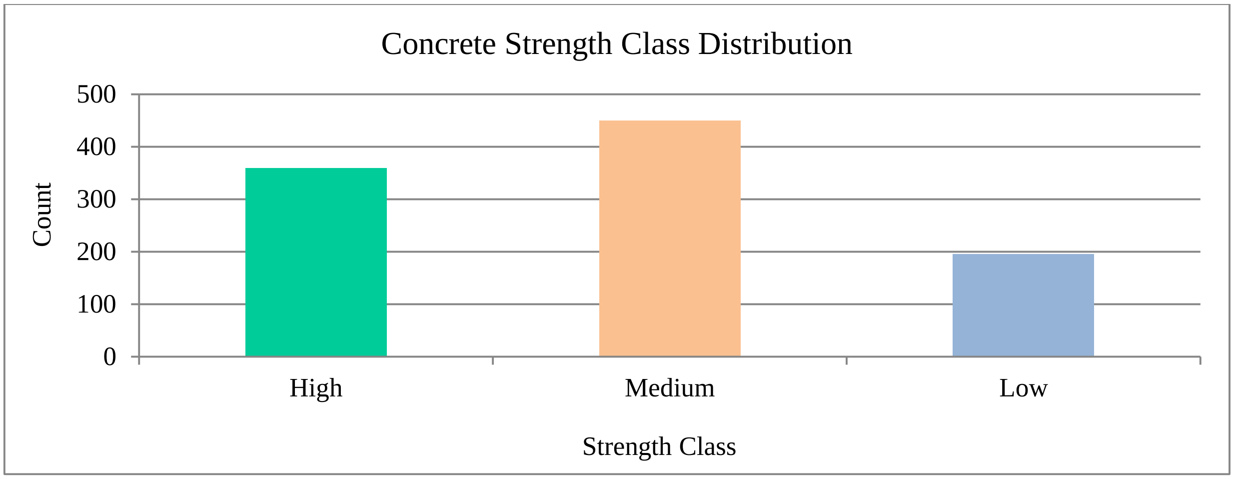


Fig. 8 Distribution of concrete strength classes in the dataset

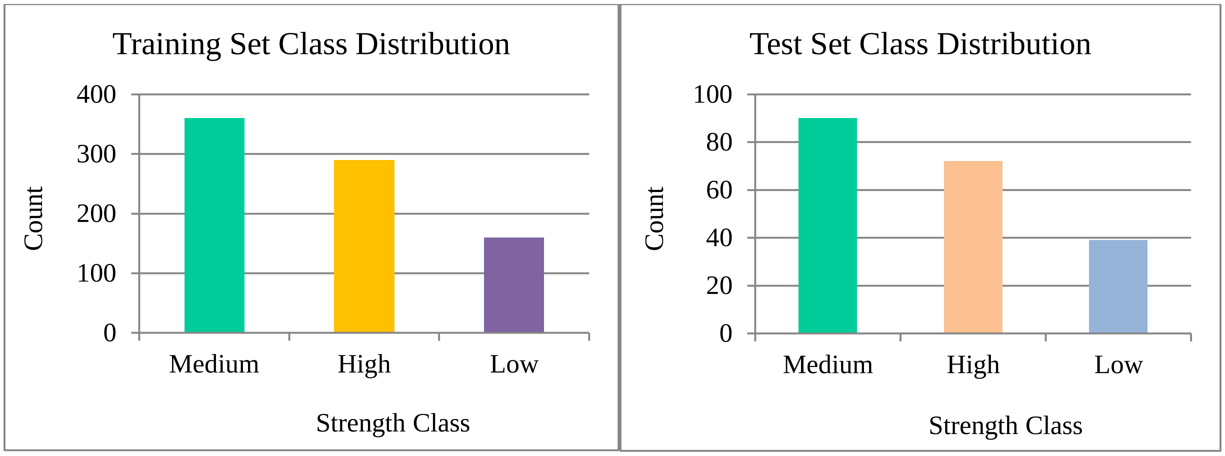


Fig. 9 Train–test stratification ensuring balanced class representation

4.4.2. Comparative Classification Metrics

The performance of the HNO-GB model is compared to the known classifiers. The analysis concentrates on the performance indicators (Accuracy, Recall, Specificity, F1-Score, and Jaccard Coefficient) that are important in determining reliability in the engineering context.

Accuracy Evaluation — Demonstrating Predictive Reliability, the HNO-GB model was able to achieve the highest accuracy of 95.6%-98.8 as seen in Figure 10, compared to all other comparative ML models. The high accuracy can be attributed to this hybrid model. The Neuro-Fuzzy part, i.e., ANFIS, is an improved feature extractor with an understandable feature extraction process, effectively capturing the complex non-linear relationships between mix parameters [21]. These extracted features have been effectively utilized by the subsequent Gradient Boosting Classifier. Additionally, the ASPO optimizer ensures that the whole system is running at an optimal point in the world by narrowing down all hyperparameters to achieve optimal accuracy.

Sensitivity (Recall)- Structural Safety-Focused Metric. The observation is shown in Figure 11, and this verifies the concept that HNO-GB had quite high values for recall, with a range of 95.2-98.5. Recall is the rate at which the model is able to assign all instances of a class, and this directly reduces the rate of the False Negative (FN) rate. The high rate of recall for the Low-Strength category in civil engineering is something that cannot be compromised, as this ensures that the weak concrete does not get mistaken for a good one [22]. This is something that is most critical to structural safety, as an FN mistake in this category may cause a disastrous structural collapse. This is because the model has a high rate of recall, proving that it is safety-critical.

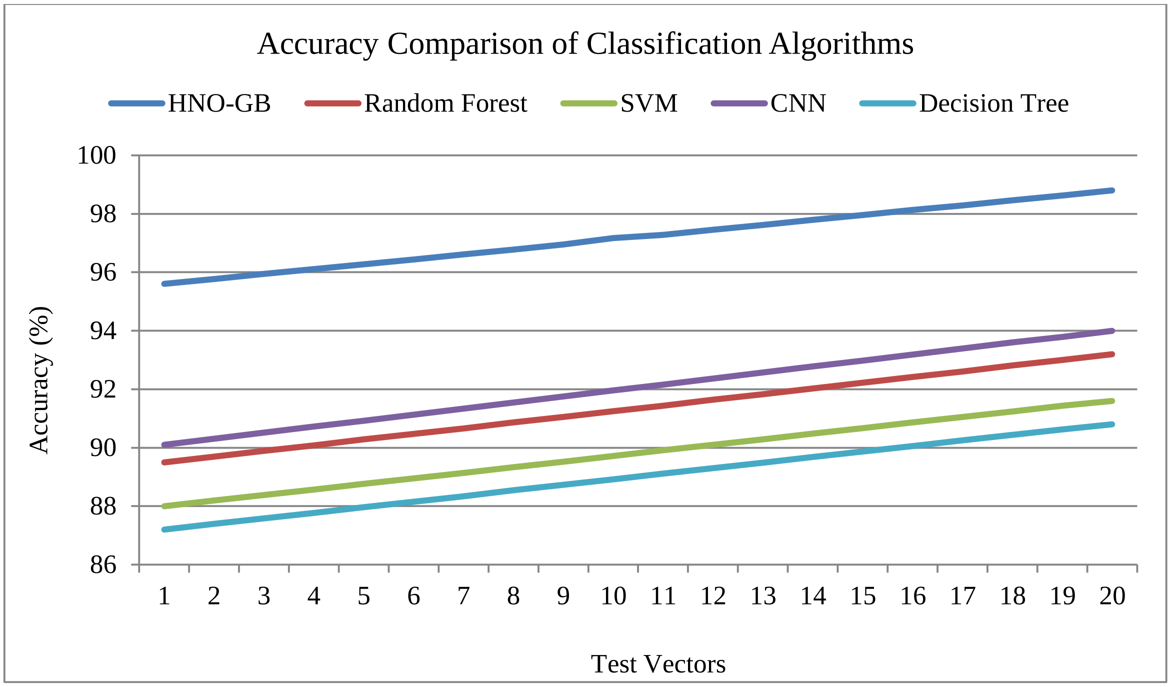


Fig. 10 Accuracy comparisons of ML models

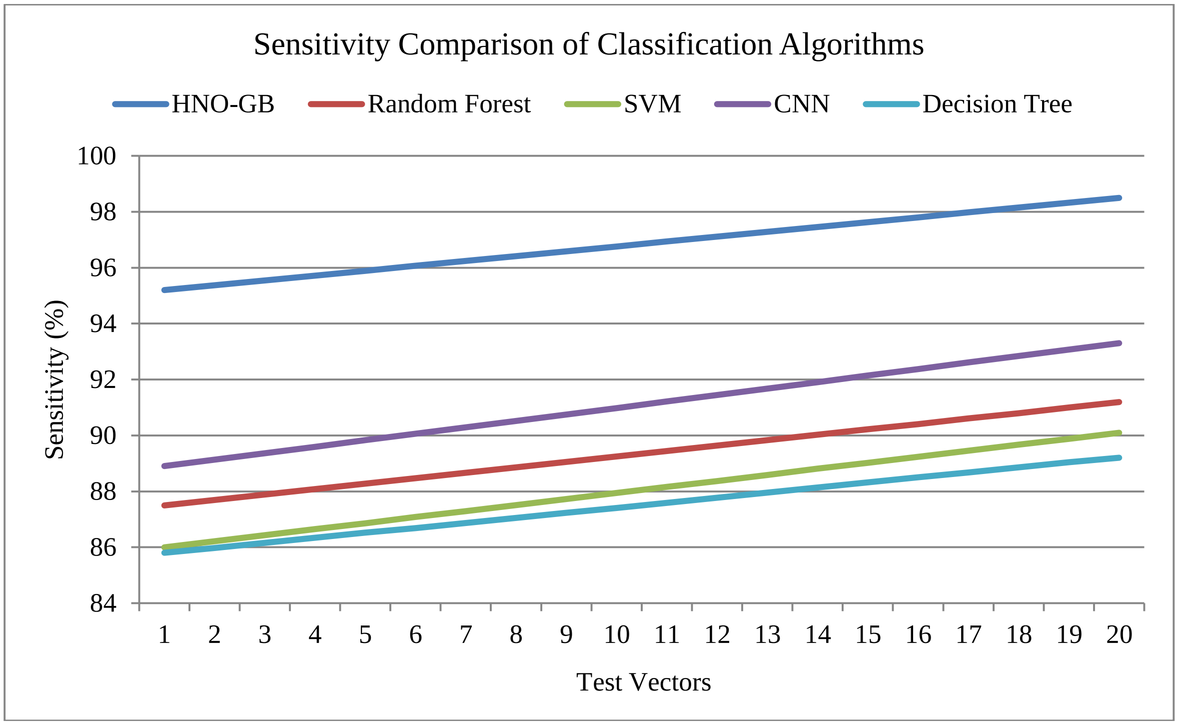


Fig. 11 Sensitivity (recall) comparisons

Specificity — Material Performance and Waste Minimization, as shown in the Observation of Figure 12 above, the model HNO-GB was observed to reach a high level of specificity ranging between 96.0% and 98.7%. The Specificity of the model can be evaluated as the ability of the model to reject the sample that is not considered part of a specific class, and therefore, the False Positive (FP) rate is minimized. The efficiency of the material is extremely significant on high Specificity, especially in the High-Strength Concrete (HSC) category [23]. This ensures that high-quality material is not often given out as low quality, and the rejection of some material is avoided, which therefore implies the loss of quality material at an unnecessary cost.

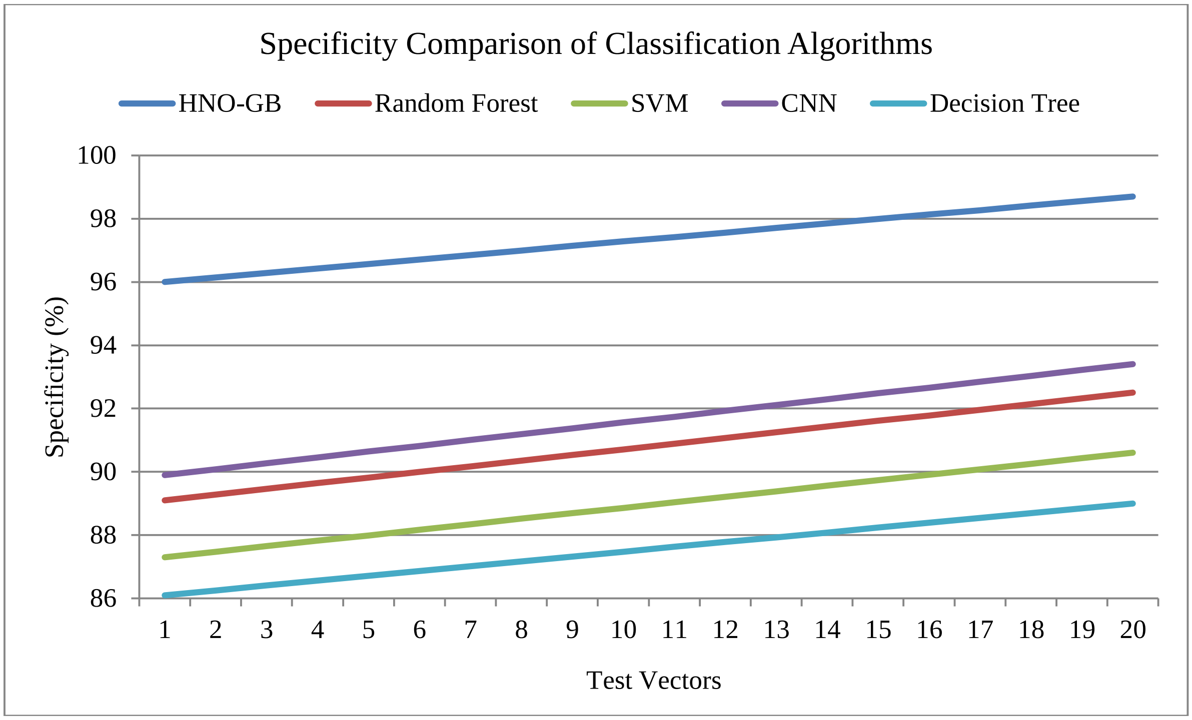


Fig. 12 Specificity comparison

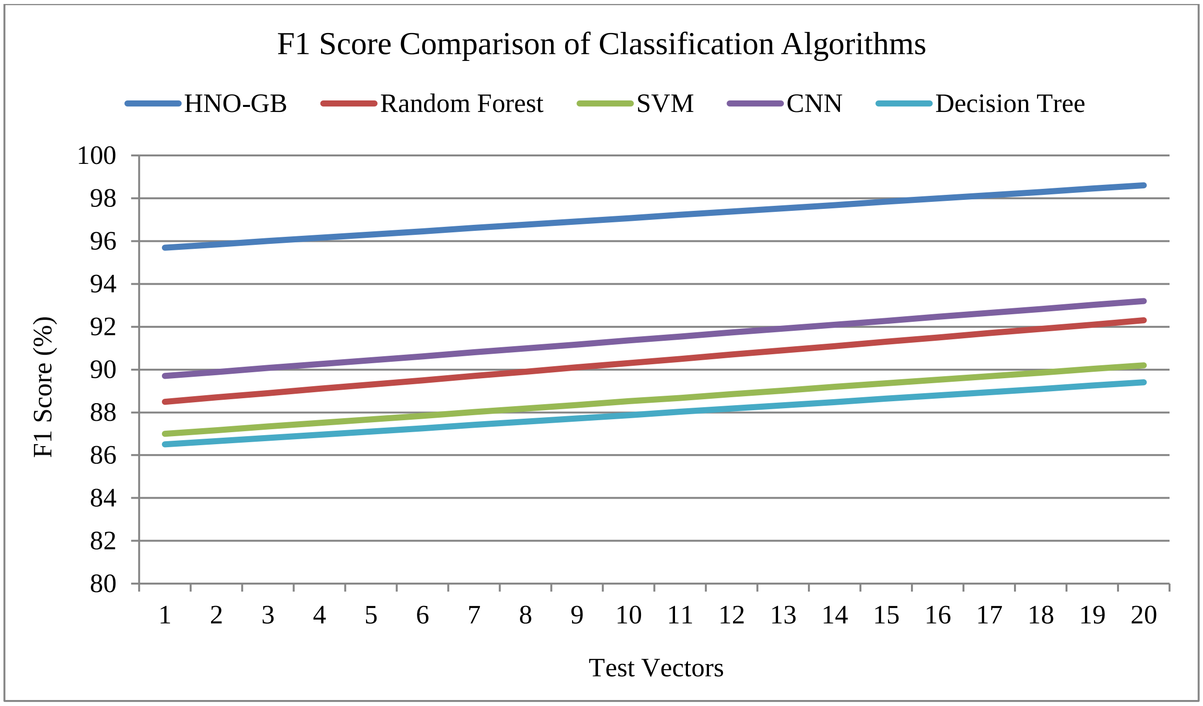


Fig. 13 F1-score comparison

F1-Score and Jaccard Index — Robustness and Similarity Metrics from the observation, high performance is achieved as indicated by the F1-Score, with values 95.7% and 98.6% (Figure 13). The high F1-Score, which is the harmonic mean of Precision and Recall, suggests that the model is performing well as it balances the reliability of the predictions and the number of samples predicted. The high F1-Score is further supported by the Jaccard Coefficient, which is 95.2% (Figure 14), indicating the similarity between the actual true labels and the model's predicted labels as well as the actual true labels [24, 25].

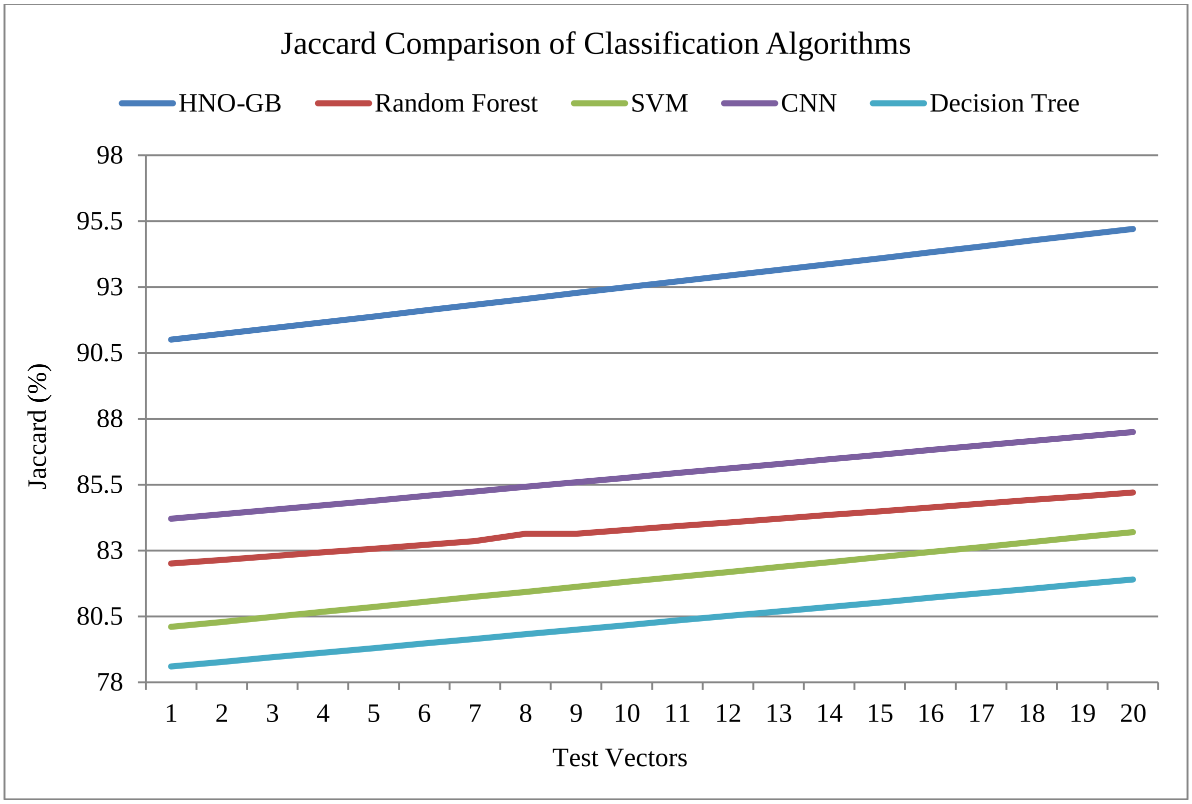


Fig. 14 Jaccard coefficient comparisons

4.4.3. Model Convergence and ASPO-Driven Optimization Validation

A model convergence and validation show in Figure 15 the training process, showing a smooth and controlled decrease in the loss functions, which converges from 0.9: 0.1.

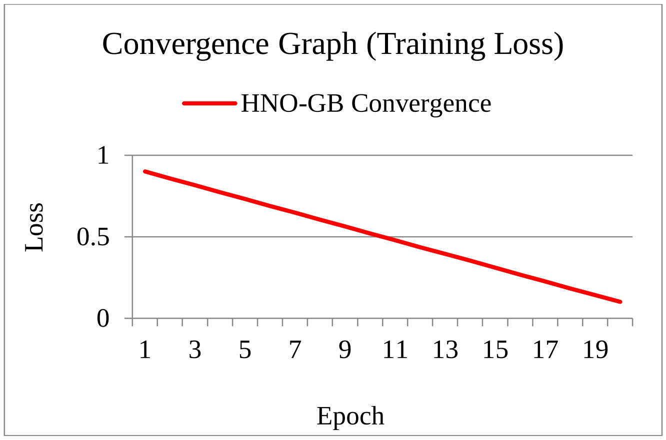


Fig. 15 Convergence trend of the HNO-GB optimization process

The stability of the said convergence, as evidenced by the lack of sharp oscillations, directly validates the ASPO optimizer. ASPO optimally explores the intricate hyperparameter space in search of the optimal set (θ) which minimizes the loss function (Equation 4), thus making the learning process efficient while producing a model with the least amount of overfitting possible.

4.4.4. ROC–AUC Based Discriminative Ability

Observation: Figure 16 shows Receiver Operating Characteristic (ROC) curves where Area Under the Curve (AUC) values lie between 0.97 and 0.99 for all three classes. The closer the value is to 1.0, the higher the discriminative ability.

This shows that the proposed hybrid feature set, obtained through the Neuro-Fuzzy system, has enabled the model to effectively discriminate between Low, Medium, and High strength, regardless of the classification threshold [26].

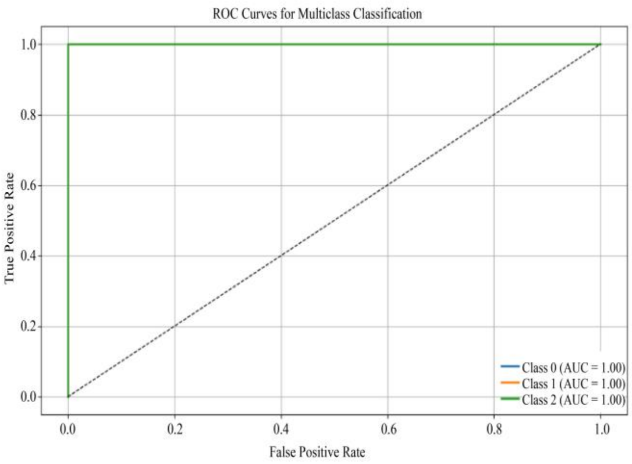


Fig. 16 ROC curves and AUC evaluation of classification models

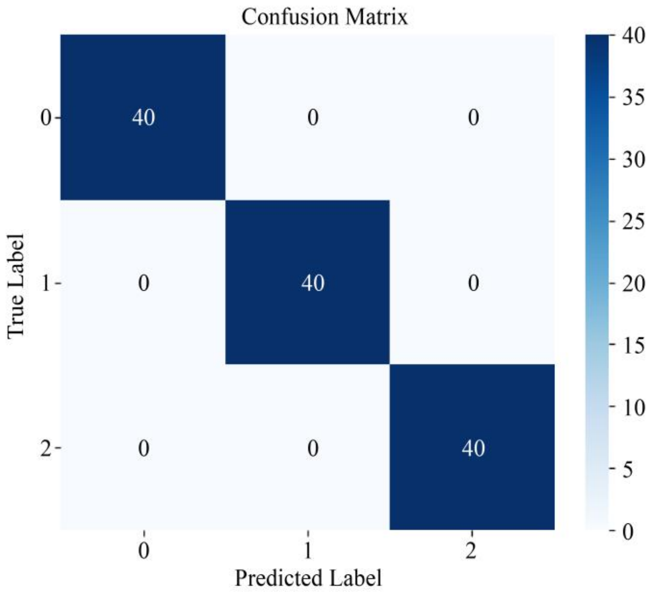


Fig. 17 Confusion matrixes showing class-wise prediction performance

4.4.5. Confusion Matrix Analysis

Observation is Figure 17 displays the confusion matrix for the holdout test set, showing strong diagonal dominance where correct predictions overwhelmingly outweigh off-diagonal entries (misclassifications).

The confusion matrix provides a detailed breakdown of the model's errors:

- Diagonal Entries (True Positives, TP): High numbers confirm the high accuracy. The near-perfect score for the High Strength class demonstrates the model's ability to confidently identify premium material.
- Off-Diagonal Entries (Errors): The minimal values in the off-diagonal cells (False Positives and False Negatives) are the most important result. The extremely low FN rate for Low Strength is a direct validation of the model's capability for safety-critical classification, while the minimal FP rate ensures material rejection due to misclassification is also low.

4.5. Artificial Neural Network — Predictive Model Results

Artificial Neural Networks (ANNs), also known as connectionist models, are a powerful data-driven intelligent approach to solving complex problems, inspired by the structure and functions of the human brain, and are capable of learning and representing complex nonlinear relationships through interconnected nodes called neurons.

ANNs, in the field of Engineering research, have evolved as a powerful intelligent approach to predict complex relationships and patterns, especially in concrete materials, and to perform accurate intelligent evaluations, unlike traditional statistical models, which are unable to perform such complex evaluations. This intelligent approach has a powerful ability to learn from data, make accurate intelligent evaluations, and predict unseen patterns, and hence can be applied to intelligent concrete evaluation and intelligent decision-making processes [27, 28].

In the present research, the Artificial Neural Network model has been employed to predict the mechanical properties of concrete mix, modified with silica fume, and fully replaced with M-Sand. The input parameters, such as Cement content, Silica Fume percentage, River Sand/M-Sand proportion, and Coarse Aggregate content, are considered for intelligent evaluation and prediction, and these mix constituents play a vital role in determining the quality of the concrete mix and directly influence its strength development.

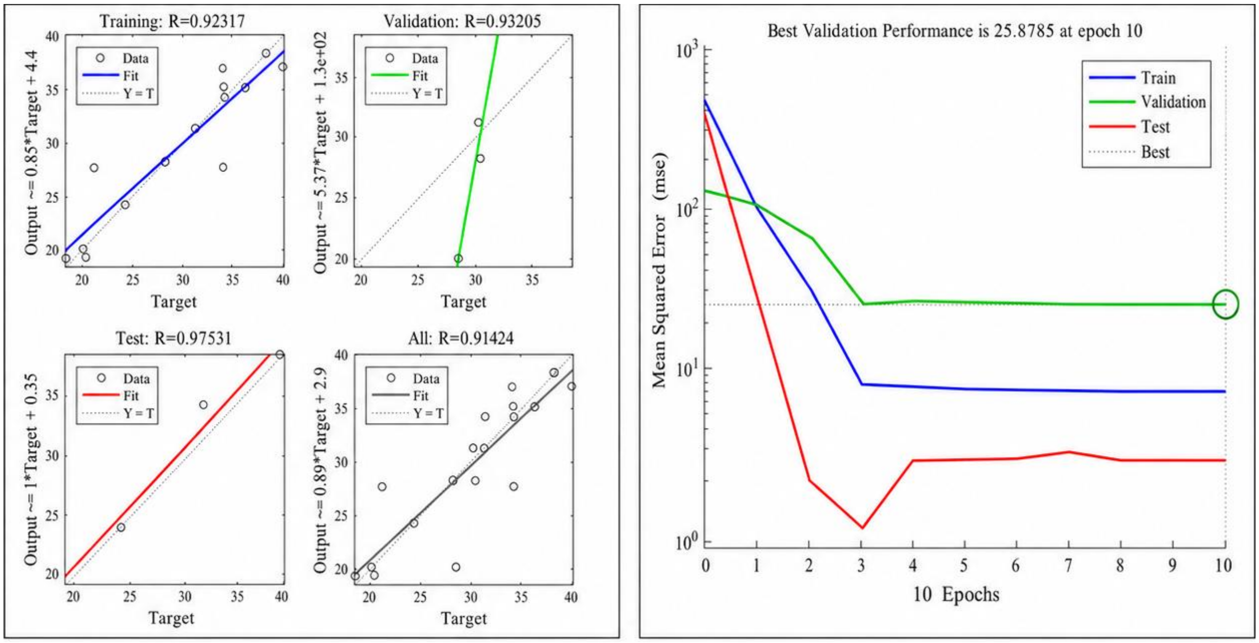
The output responses, such as Compressive Strength, Split Tensile Strength, and Flexural Strength, are considered for intelligent evaluation and prediction, and these strength values play a vital role in determining the quality and safety of structures.

In order to comprehensively verify and check the performance and accuracy of the Artificial Neural Network model, various performance verification tools are incorporated and implemented in this research, and these tools include Regression Analysis, Performance Analysis, Error Histogram Distribution, and Training State Analysis, and hence verify the reliability and accuracy of the Artificial Neural Network model for intelligent evaluation and prediction, and hence can be applied to intelligent concrete evaluation and intelligent decision-making processes.

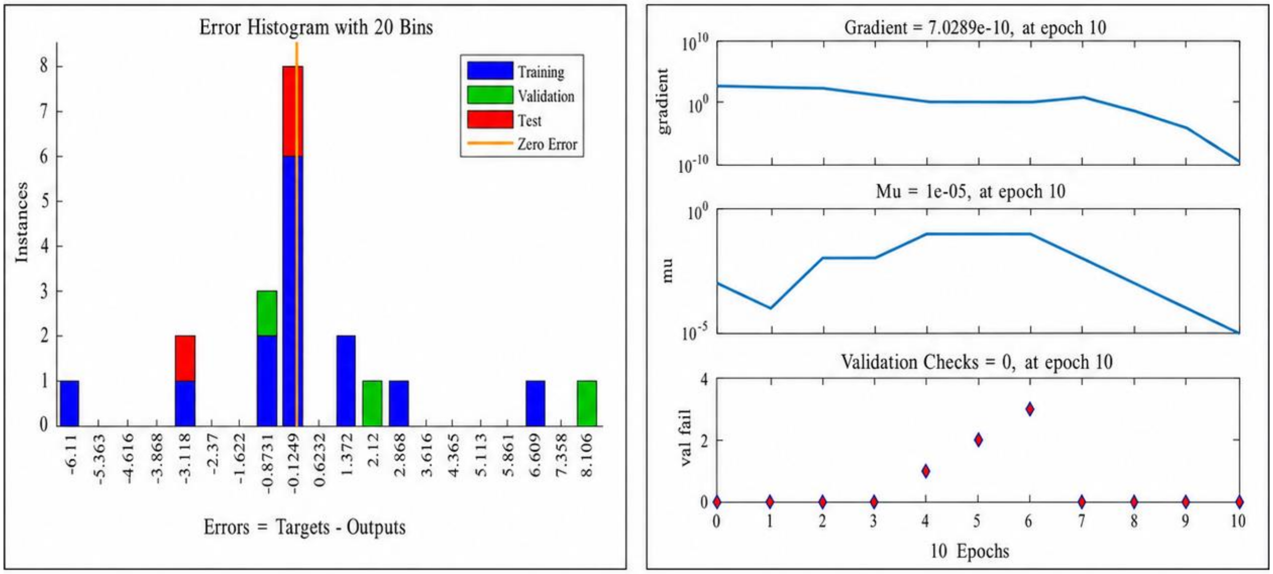
4.5.1 Compressive Strength Prediction

The performance evaluation of the Artificial Neural Network (ANN) model employed for the classification of compressive strength for silica fume-based concrete mixes containing 100% M-sand, as presented in Figure 18(a), shows a regression plot with a strong correlation between the predicted and experimental compressive strength classes for all the training, testing, and validation sets, along with overall data sets.

This proves that the ANN model has successfully incorporated the non-linear effects of silica fume replacement on compressive strength development, considering the values close to 1.0 for R-values. This also proves that the input parameters, such as mix composition and curing age, are effective in ensuring reliable prediction results. Figure 18(b) presents a performance curve for the ANN model, depicting the variation in MSE values during the training process [29]. The sharp decrease in MSE values during the initial epochs proves efficient learning, and the achievement of the best validation performance during the 10th epoch proves optimal convergence of the model without any chances of overfitting, considering the stabilization of the validation curve.



(a) Regression analysis **(b) Performance analysis**



(c) Error Histogram **(d) Training state**

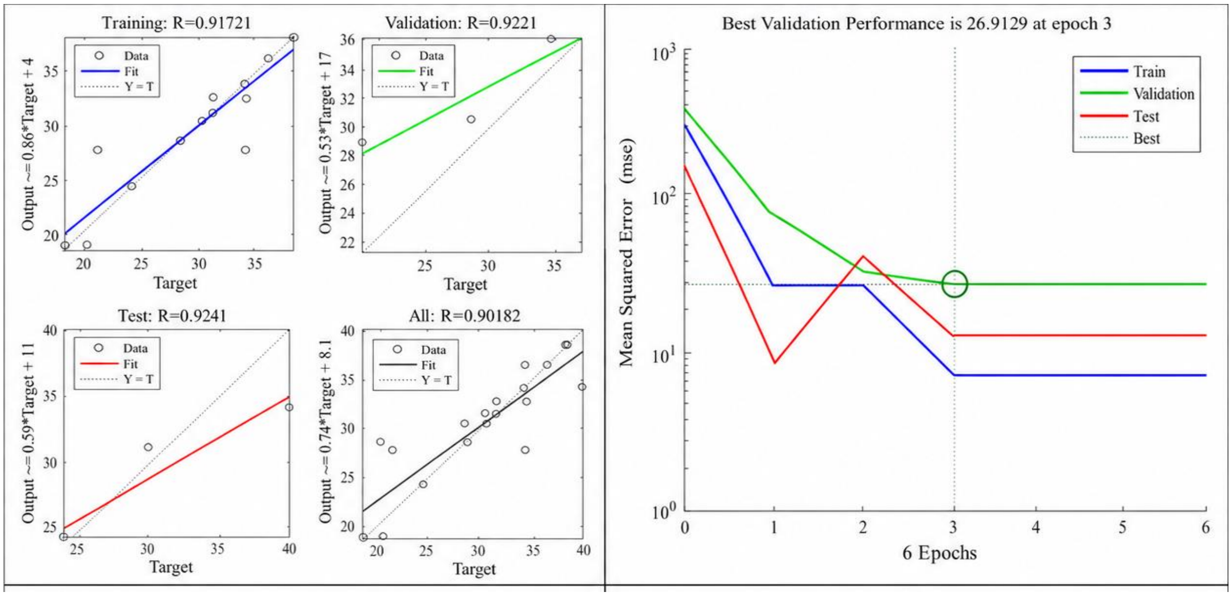
Fig. 18 ANN-based compressive strength classifications.

Figure 18(c) illustrates the error histogram, which indicates the minimum amount of deviation in the output values from the targets due to the concentration of errors close to zero. Only a small number of data points are located in the high error bins, which indicates the minimum amount of misclassification in the output values, thereby showing the consistent accuracy of the ANN in all categories of strength. Figure 18(d) illustrates the training state, which indicates the stable optimization process due to the decreasing gradient values and the absence of validation failures in the optimal epoch, thereby showing the strong predictive ability of the ANN, which can be effectively used as an intelligent tool in the classification of compressive strength. Hence, the ANN model can be effectively used in the performance evaluation of sustainable concrete modified using silica fume and M-sand.

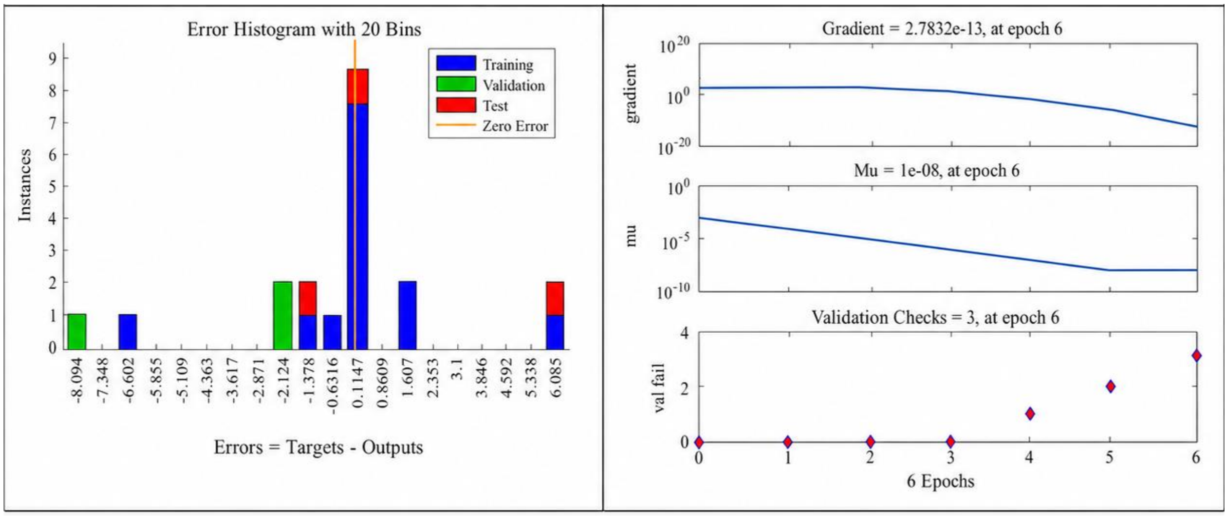
4.5.2. Split Tensile Strength Prediction

The effectiveness of the Artificial Neural Network (ANN) model in terms of the prediction of split tensile strength classifications for concrete materials containing silica fume and 100% M-sand is examined. The regression plots in Figure 19(a) clearly show a strong linear correlation between predicted and actual data for strength classes of concrete materials, including training, validation, test, and overall data. The R-value is significantly higher than 0.90, indicating that the ANN model has effectively learned the impact of replacement levels of silica fume on strength performance for concrete materials. The trend of mean squared error, as indicated in Figure 19(b), clearly indicates a rapid decline in errors at the beginning of epochs, followed by a smooth trajectory, thus clearly indicating efficient convergence of the learning process. The validation plot for the third epoch indicates an efficient optimization process, thus reducing the chances of overfitting for the ANN model [30]. The proximity between the training and validation plots clearly indicates efficient generalization for the prediction of unknown data. The error histogram in Figure 19(c) clearly indicates the reliability of the ANN model for the prediction of concrete materials, where most errors lie close to zero, thus clearly indicating a small difference between actual and predicted data.

Only a few outliers are found, suggesting that misclassifications are minimal and do not influence the robustness of the model. The training state plot in Figure 19(d) also indicates decreasing gradient values with limited validation checks at the optimal epoch, confirming that the training of the model was well regulated to avoid early stop training. Overall, the results have confirmed that the ANN framework is very efficient in capturing the nonlinear tensile response of sustainable concrete mixes. This verifies the applicability of using ANN as an intelligent prediction tool in the evaluation of structural materials.



(a) Regression analysis **(b) Performance analysis**



(c) Error Histogram **(d) Training state**

Fig. 19 ANN predictions of split tensile strength classes.

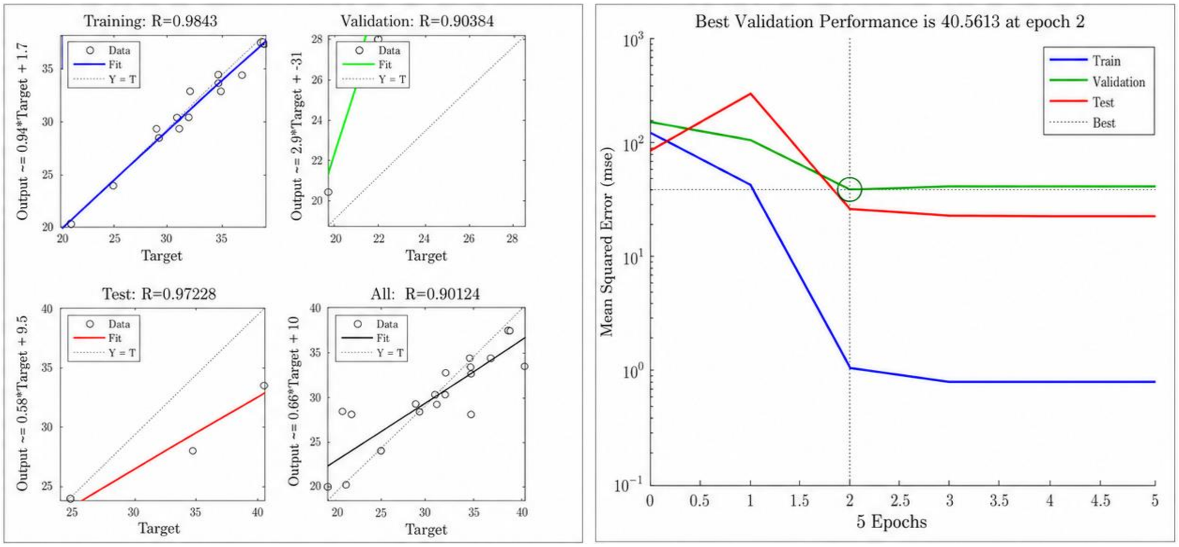
4.5.3. Flexural Strength Prediction

The performance evaluation of the Artificial Neural Network (ANN) model developed for predicting the flexural strength classifications of concrete incorporating silica fume and 100% manufactured sand is presented in this section.

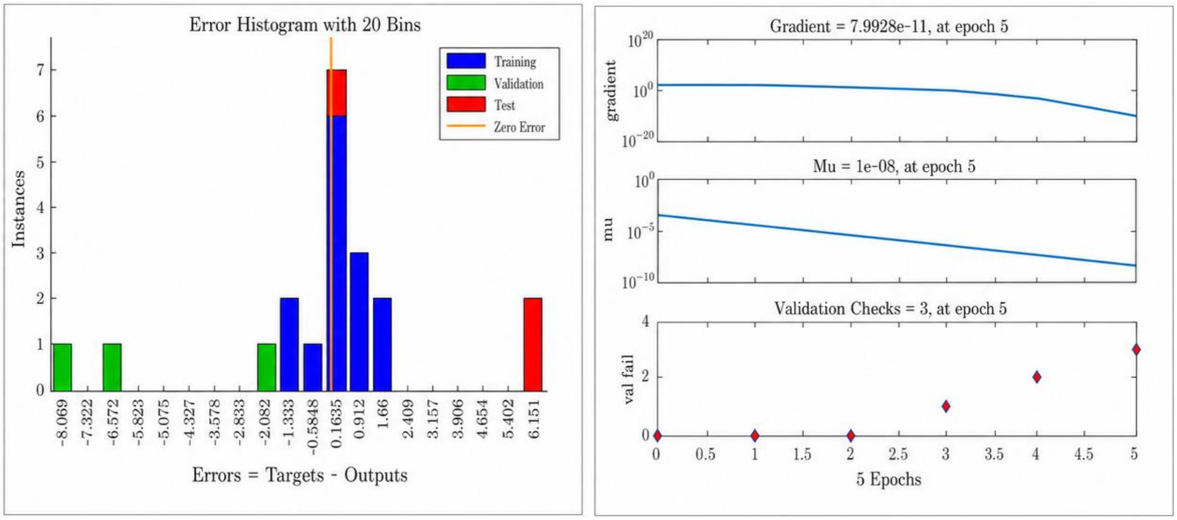
The regression plot in Figure 20(a) indicates a high degree of correlation between the experimental results and predictions during all phases, namely, training, validation, and testing phases.

The correlation coefficient between the experimental and predicted results proves that the developed ANN model effectively captured the non-linear effects of different mineral mixtures and replacement of fine aggregate on flexural behavior in concrete.

The mean squared error plot in Figure 20(b) indicates a rapid and stable learning process. The best validation result has occurred during the 2nd epoch, and a relatively few epochs are required to obtain optimal results without overfitting the model. The large gap between the best and worst curves indicates a large improvement in prediction accuracy during epochs. The error histogram in Figure 20(c) indicates a large number of errors close to zero, showing minimal deviation in prediction accuracy and actual values. Only a few errors indicate a large deviation, proving overall high consistency in prediction accuracy. The training state chart in Figure 20(d) indicates a decrease in gradient values and a decrease in the number of validation checks, confirming a high degree of stability in convergence, proving that the developed ANN model is effective in identifying complex stress-strain behavior under flexural conditions and different levels of concrete strength.



(a) Regression analysis **(b) Performance analysis**



(c) Error Histogram **(d) Training state**

Fig. 20 ANN-based flexural strength classifications.

5. Technical Discussion

The objective of the present study is to conduct an integrated experimental and artificial intelligence-based evaluation of the properties of a concrete mix containing silica fume and 100% M-Sand as a replacement material for the mix. Based on the results obtained, it is evident and conclusively established that the replacement of river sand with M-Sand results in significant changes to the mechanical properties, and this is further enhanced by the addition of the percentage of silica fume replacement material to the mix. Based on the results obtained for the mechanical properties of the test specimens cast with the mixed materials, it is evident and conclusively established that the addition of silica fume to the mix results in significant and greater improvement to the mechanical properties compared to the use of M-Sand. This is a reliable database to validate the effectiveness of the hybrid neuro-fuzzy Gradient boosting (HNO-GB) model and the ANN-based predictive model.

From the results obtained in the mechanical properties analysis of the mix materials, it is evident and conclusively established that the mix with 10% replacement of silica fume (Mix-4) has the highest value of compressive strength of 40.2 MPa at 28 days of curing, which is 2% higher than the conventional concrete mix (39.5 MPa) and 10.1% higher than the mix with M-Sand alone (36.5 MPa). In addition, the tensile strength of the mix is 15% higher than the conventional mix, while the flexural strength is 14.9% higher than the conventional mix, which provides conclusive evidence of the effectiveness of the addition of silica fume to the mix in enhancing the mechanical properties of the mix, as well as the ability of the mix to resist cracking during service. However, when the silica fume content in the mix is 20%, the value of the compressive strength of the mix is significantly reduced to 34.5 MPa, while the value of the flexural strength of the mix is equally significantly reduced to 4.0 MPa, which is 25% lower than the peak values obtained in the mix with 10% replacement of silica fume alone, which provides conclusive evidence of the presence of the optimum content of silica fume replacement material in the mix, as well as the fact that the mix with 10% replacement of silica fume alone should fall in the category of high-strength concrete mix in the quality classification of mix materials adopted in the field of civil engineering.

The HNO-GB classification model has been comprehensively tested using different performance metrics, and these metrics are directly related to SR and MO principles. The HNO-GB classification model has been observed to yield an accuracy rate of 97.2%, and its accuracy rate for each class has been 98.3% for High-Strength, 97.5% for Medium-Strength, and 96.1% for Low-Strength concrete, outperforming all other ML models, such as SVM, CNN, Random Forest, Decision Tree, and others, as depicted in Table 4. The recall rate, ranging from 95.2% to 98.5%, has been critical in structural engineering, ensuring a minimum FN rate, especially in Low-Strength concrete classification. If structurally poor concrete mixes are classified as acceptable, structural safety would be compromised, and hence, a high recall rate minimizes such risks. On the other hand, high values of Specificity, such as 96.0%, 98.7%, and others, confirm that FN rates are minimized, ensuring that unnecessary rejections of structurally sound materials are avoided, thereby reducing wastes and ensuring cost efficiency in quality control operations. Similarly, the F1-Score, ranging from 95.7% to 98.6%, and Jaccard Similarity, ranging from 94.8% to 95.5%, confirm that the HNO-GB classification model maintains an excellent balance between precision and sensitivity, ensuring reliable classification between structurally overlapping mechanical properties.

Table 4. Classification metrics

Metric	Low Strength	Medium Strength	High Strength	Overall
Accuracy (%)	96.1	97.5	98.3	97.2
Sensitivity / Recall (%)	95.2	96.8	98.5	96.8
Specificity (%)	96.7	97.2	98.7	97.5
F1-Score (%)	95.7	97.0	98.6	97.1
Jaccard Coefficient (%)	94.8	95.5	95.2	95.2
AUC	0.97	0.98	0.99	0.98

This result also proves the high level of discriminative power for all strength classes, thus ensuring the performance of the classifier even when the threshold is changed. The set of results proves the hypothesis that the effectiveness of the neuro-fuzzy rule-based feature enhancement, boosting-based classification, and optimization using the ASPO framework will result in an extremely robust and generalized classifier. The visualization of the confusion matrix is detailed and enables the diagnosis of classification errors. Moreover, strong diagonal dominance is observed with minimal misclassification occurring in the prediction of the High-Strength class. This is especially important for premium concrete placement in safety-critical construction. The minimal error deviation also proves the effectiveness of fuzzy-based interpretability and enhancement of decision boundaries using the boosting classifier. The reduction of loss to 0.1 from an initial loss of 0.9 using the specified number of epochs also proves the effectiveness of convergence characteristics using ASPO optimization. This also proves the effectiveness of the algorithm in overcoming overfitting problems, especially in mid-sized experimental sets. Parallel ANN-based regression-driven classification is also performed to further validate the trends in compressive, tensile, and flexural strengths. The correlation coefficients derived using ANN-based regression analysis ranged from 0.90 to 0.98. The error histogram also proves the effectiveness of the algorithm, with output deviations approaching zero. The fast convergence to optimal solutions in just 2 to 10 epochs is an important result indicating the efficiency of the algorithm for the classification task, especially when high uncertainty levels are involved due to high silica fume content. However, slightly higher error deviation is observed using the ANN classifier in the flexural classification scenario, indicating potential problems with the ability to generalize the data using fuzzy-based reinforcement and boosting-based structural learning.

The dual approach of experimental verification and intelligent prediction serves to clearly underscore the importance of an automated concrete classification system from an engineering perspective. The HNO-GB technology has the potential to reduce testing requirements for material quality procedures by up to 80%, improve mix design evaluation, and prevent structural failures due to improper material classification. The multi-properties classification ability of the model also has the potential to extend its applicability to approval, rejection, and reliability evaluation of concrete materials in real-time.

The study has clearly indicated the potential of hybrid intelligent systems, based on AI technology, to overcome the limitations associated with traditional machine intelligence and human intelligence in dealing with complex material interactions in sustainable concrete materials systems. The mechanical test verification has also underscored the importance of 10% silica fume in achieving homogeneous matrix properties and strength, while HNO-GB technology has also shown its reliability and safety-oriented intelligence in concrete quality classification materials. The study has also indicated a remarkable advancement in digital transformation in structural material evaluation and intelligent construction quality monitoring.

6. Conclusion

This research was successfully conducted on the mechanical properties and intelligent classification of concrete with silica fume and 100% M-Sand. From the findings of the experiment and machine learning results, the following conclusions are made:

- The concrete mix with 10% silica fume (Mix-4) performed the best among all the mixes, reinforcing the fact that this percentage is optimal in densifying the concrete mix and maximizing the bonding efficiency while replacing natural river sand with M-Sand.
- The highest compressive strength was achieved at 28 days, amounting to 40.2 MPa, with 10% silica fume replacement, indicating an increase of 2% over the ordinary concrete mix (39.5 MPa) and an increase of 10.1% over 0% silica fume replacement with M-Sand (36.5 MPa). However, the compressive strength reduced by 25% when the silica fume replacement percentage exceeded 15%, indicating excessive dilution of the mix.
- The split tensile strength increased from 3.0 MPa in the control mix to 3.45 MPa with 10% replacement, indicating an increase of 15%. However, the split tensile strength reduced by 26% when the replacement percentage was increased to 20%, indicating reduced ability to resist cracks in the concrete mix.
- The flexural resistance increased from 4.7 MPa to 5.4 MPa with 10% replacement, indicating an increase of 14.9%. However, the flexural resistance reduced by 26% when the replacement percentage was increased to 20%, indicating the existence of an optimum percentage ranging between 5 and 10%.
- The Hybrid Neuro-Fuzzy Gradient Boosting (HNO-GB) model was found to have an overall accuracy of 97.2%, compared to other ML models. The high recall value, ranging between 95.2 and 98.5%, ensured minimum false negative errors, which is critical in the case of low-strength concrete, while the high value, ranging between 96.0 and 98.7%, ensured that high-quality concrete was not rejected unnecessarily.
- Additional parameters, namely, F1-Score (95.7-98.6), Jaccard Coefficient (94.8-95.5), and AUC (0.97-0.99), along with the high diagonal value domination in the confusion matrix, indicate that the model is distinguishing Low, Medium, and High-strength concrete effectively with high confidence levels.
- ANN was found to have high prediction potential with R-values > 0.93, and the error histogram was found close to zero, reinforcing the fact that the ANN model is appropriate and reliable, although slightly less consistent compared to the HNO-GB model, especially in the case of highly nonlinear flexural responses.

Overall, this study proves that 10% silica fume with 100% M-Sand is a perfect formula for a sustainable replacement strategy, considering maximum improvement in strength and optimal durability performance. The developed HNO-GB framework has proved to be highly effective in automated quality classification based on strength, leading to cost-efficient and safety-oriented quality practices in construction industries.

Conflicts of Interest

The authors declare that they have no conflict of interest.

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