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Research Article

Performance assessment of polypropylene fiber-reinforced engineered cementitious composites using experimental investigation and ANN modeling

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ABSTRACT

The use of engineered cementitious composites (ECC) in structural repair and rehabilitation is becoming more and more common because of their strain-hardening behavior, controlled cracking, and better durability. Polypropylene fiber-reinforced ECC has even more benefits like being resistant to corrosion and saving money, however its mechanical performance is very much affected by the changes in mix composition and the amount of fiber used in the mix. The traditional approaches in mix design are mostly based on either carrying out large-scale experimental trials or using complex micromechanics-based formulations, which are both time-consuming and not very applicable in practice. On the other hand, although the use of Artificial Neural Networks (ANNs) for modeling the behavior of different cement-based materials has been successful, its use in the case of polypropylene fiber-reinforced ECC is still limited. The present study aims to develop an ANN-based predictive framework to predict compressive and flexural strength of polypropylene fiber-reinforced ECC by using the parameters of the mix design. A detailed experimental program with compressive strength and three-point bending tests was performed with different polypropylene fiber contents to study the ECC mixtures. ECC mixtures containing 0–2.0% PP fibers were experimentally tested at curing ages of 14, 28, and 56 days. The results indicate that an optimum PP fiber content of 1.5% yielded the highest mechanical performance, achieving compressive strengths of 31.95 MPa, 47.95 MPa, and 50.61 MPa, and corresponding flexural strengths of 13.41 MPa, 17.50 MPa, and 24.12 MPa at 14, 28, and 56 days, respectively. For making the model more robust and generally applicable, the experimental results were merged with the data from published literature that was carefully selected for ANN training and validation. An ANN model trained using 105 datasets (experimental and literature-based) demonstrated strong predictive capability, with coefficients of determination (R^2) of 0.955 and 0.963 for compressive and flexural strength during training, and 0.953 and 0.975 during testing, respectively. The mean absolute percentage error remained below 8.2% for both strength parameters. The proposed model shows a very strong agreement between the values of strength predicted and those measured in the experiments, as it is able to capture the non-linear relationship between the composition of ECC and its mechanical performance. The framework that has been developed is a practical tool for the optimization of ECC mixes and assessment of their performance, particularly for applications involving the rehabilitation of buildings where accurate predictions and efficient design of materials are of utmost importance.

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1. Introduction

Critical infrastructure construction is greatly relying on cementitious materials, which are the most easily available, least costly, and strongest in compression among all construction materials. However, traditional cement-based concretes display a quasi-brittle behavior with very low tensile strength, thus they crack and fail suddenly under dynamic and impact loads. The above shortcomings have a negative impact on the lifespan of the structure, maintenance, and serviceability, therefore the search for new cementitious materials with better ductility, crack control, and damage tolerance is encouraged.

Concrete has been in great demand and the construction industry has been developing so fast that its demand is now even higher. The use of concrete in infrastructures and buildings is a factor that has led to its massive global production. Ordinary concrete is made mainly of cement, fine and coarse aggregates and is characterized by its very good compressive strength but at the same time very weak tension. That is why different methods for strengthening concrete, such as using steel reinforcement, are widely applied in making the material able to withstand tension and cracks. The scenario of concrete has changed and the need for high-strength concrete has also increased very quickly due to modern construction practices with their own performance demands. On the contrary, research has shown that conventional concrete becomes more brittle as its compressive strength increases, which limits its application to non-ductile areas. The need to counter this problem has led to the introduction of new advanced cementitious materials with superior ductile behavior, such as the use of engineered cementitious composites (ECC), which are now being considered for structural and rehabilitation purposes (Uddin et al. 2024).

Engineered cementitious composites have turned out to be a new type of high-performance material that can effectively eliminate the drawbacks of the traditional construction materials (Li et al. 2001). ECC is one of the very few composite that can withstand high tensile strain and at the same time develop many tiny microcracks with precisely controlled widths, instead of large localized cracks. In contrast to regular concrete, ECC generally does not contain any coarse aggregates and depends on a very carefully controlled mixture of cementitious binders, fine aggregates, and short discrete fibers to attain the desired enhancement in mechanical performance. Because of these characteristics, ECC, which is often known as flexible concrete, has not only been that much utilized in the above-mentioned fields but also in structures, bridge decks, seismic-resistant systems, and repair and refurbishment where ductility and durability are the main requirements.

Extensive studies have demonstrated that fiber-reinforced ECC exhibits superior tensile strength, pseudo strain-hardening behavior, and high energy absorption capacity when compared to conventional fiber-reinforced concretes (Liu et al. 2023). The mechanical performance of ECC is highly influenced by the properties of the fibers and the composition of the mix (Wang and Li 2006; Yu et al. 2015). As a result, research has been conducted on the performance enhancement of ECC under compression and tension loading with the addition of polypropylene fiber (PP) (ChiaHwan and JianBo 2014; Hossain et al. 2024; Zhu et al. 2021). Among various fiber types, polypropylene fibers have attracted increasing attention due to their low density, corrosion resistance, cost-effectiveness, and favourable interaction with the cementitious matrix. ECC mixtures incorporating polypropylene fibers in the range of 0–2.0% by volume has been reported to show notable improvements in flexural performance, ductility, and crack resistance. In addition, ECC systems incorporating functional fibers have demonstrated self-sensing and multifunctional capabilities, further expanding their application potential (Han et al. 2015).

Despite these advances, the mechanical and functional properties of ECC remain highly sensitive to variations in mix design parameters, fiber volume fraction, and constituent material proportions. The exact forecasting of prominent performance measures like compressive strength, flexural strength, and crack behavior based solely on mix composition remains one of the hardest problems to solve. Nevertheless, micromechanics-based theories do help in the design of ECC somewhat by connecting fiber–matrix interactions to macroscopic behavior (Fischer and Li 2007), however, their application in practice is frequently restricted by requirements such as detailed microstructural calibration, huge experimental validation, and numerical simulations.

The research on engineered cementitious composites has moved from purely strength enhancement to much more diverse fields including crack control, durability, multifunctionality, and data-driven material design. At the same time, the enhancement of the mix optimization methods, supplementary cementitious materials, and microstructural tailoring have all contributed to the sustainability and applicability of ECC. The material innovations are not the only factor, there is also the growing adoption of artificial intelligence techniques, such as neural networks and machine learning regression models, which have been used to predict the mechanical and durability properties of cement-based materials. The use of these techniques has proven to be highly effective in identifying nonlinear relationships, which are usually difficult to pinpoint with either analytical or empirical models. This study is moving the field of ECC forward by combining experimental research with ANN-based modeling, thus making ECC research relevant to contemporary data-driven material design and simultaneously solving the issue of performance prediction.

In the past few years, Artificial Neural Networks (ANN) have been acknowledged as the best means for modeling intricate and non-linear relationships among materials based on cement. The brain-inspired development and the ability of ANN to perform tasks simultaneously make it ideal for handling problems with analytical models that are not competent enough. Models that are built using ANN approach have already been tested and proven to predict mechanical properties of a number of cementitious systems, such as confined concrete columns (Oreta and Kawashima 2003), self-compacting concrete (Nehdi et al. 2001), elastic modulus and concrete strength (Demir 2008), autoclaved aerated concrete (Michelini et al. 2023), fiber-reinforced concrete (Ashwini et al. 2024; Kavya et al. 2022) and GGBS-based concrete composites (Bilim et al. 2009; Kavya et al. 2025). These works are the testimony of the capability of ANN models to accurately represent the nonlinear behavior of materials. However, the direct application of ANN techniques to engineered cementitious composites, particularly polypropylene fiber-reinforced ECC (Haque et al. 2024), remains limited. Unlike conventional and generic fiber-reinforced concretes, ECC behavior is governed by distributed micro-cracking and strain-hardening mechanisms, which are not explicitly addressed in most existing ANN studies.

Recent research on ECC has focused on expanding its mechanical performance, sustainability, and predictive modelling capabilities. A recent comprehensive review highlights advancements in ECC properties, design strategies, ductility performance, sustainability measures, and applications in structural engineering, including tensile strain capacities up to 8% and improved crack control behavior (Odeyemi et al. 2025). Statistical evaluations of ECC mixes with various fiber types, including polypropylene, PVA, and glass fibers at different percentages, have provided insights into the influence of fiber type and dosage on mechanical and fracture performance (Shabakhty et al. 2024). Sustainable ECC formulations using high slag and polypropylene fiber contents have demonstrated tensile strain exceeding 3% and improved energy absorption with additional mesh reinforcements (Saljoughian et al. 2024). In parallel, recent machine-learning approaches have been developed to predict ECC mechanical behavior beyond conventional strength measures, including ANN-based models for full tensile stress–strain curves and ANN predictions for polyethylene fiber–based ECC performance. These studies reflect emerging trends in ECC research, incorporating advanced materials, sustainability considerations, and data-driven predictive modelling (Riaz et al. 2023).

The innovation of this research is to the extent of the combined experimental and soft computing methods that were used to assess and forecast the mechanical performance of polypropylene fiber-reinforced ECC. The current study carries out systematic integration of experimentally generated data with chosen literature data to create a strong and all-encompassing dataset. An ANN based predictive model is created and statistically verified for the purpose of providing an accurate estimate of compressive and flexural strengths, based on the parameters of mix design. The nonlinear influence of key mix design parameters on compressive and flexural strength is captured by the proposed model in a way that reflects ECC-specific deformation mechanisms through the integration of these data sources. This framework establishes a direct data-driven relationship between the composition of ECC and its mechanical performance without the need for complex micromechanical assumptions or extensive trial-and-error testing.

Despite extensive research on engineered cementitious composites, limited studies have systematically investigated the combined effects of polypropylene fiber content on mechanical performance, microstructural behavior, and predictive modeling within a unified framework. In particular, the majority of existing studies focus either on experimental strength characterization or on data-driven modeling, with minimal integration of SEM-based microstructural evidence to explain strength enhancement mechanisms. Furthermore, ANN models specifically developed for polypropylene fiber-reinforced ECC remain scarce. Therefore, the present study addresses this gap by experimentally evaluating compressive and flexural behavior, correlating microstructural observations with mechanical performance, and developing an ANN-based predictive model, thereby providing a comprehensive understanding of polypropylene fiber-reinforced ECC.

2. Materials and Method

The mechanical properties of bendable concrete are influenced by the combination of the fiber strength, its elastic modulus, interaction between the fiber and matrix, fine particles and cement paste. To carry out the experimental inquiry, multiple ratios of cement, fly ash and fine aggregates were adopted as per the relevant Indian Standards. Moreover, high-range water-reducing agent was added to the concrete mix for the purpose of improving the workability and the durability of the concrete. This ensured that the compatibility with building components was optimized for the water content. Polypropylene fibers are incorporated in the concrete to minimize cracking due to drying shrinkage as well as plastic. The fine dispersion of fiber helps to limit water percolation by clogging channels like pores and capillaries, thus restricting the movement of water through the concrete matrix. The properties of the polypropylene fiber are detailed in Table 1.

Table 1. Properties of polypropylene fiber.

Fiber type	Tensile strength (MPa)	Young's modulus (GPa)	Fiber elongation (%)	Specific gravity
Polypropylene	500~700	6~7	20	0.91

3. Experimental Procedure

In the initial stage of ECC preparation, the dry constituents Portland cement, fly ash, and fine sand were proportioned by weight in the ratio of 0.8:1.0:1.1, respectively. A high-range water-reducing admixture was added at a dosage of 0.1 by weight of cement. The water content was maintained separately using a constant water–cement ratio of 0.46 for all mixes to ensure adequate workability and uniform dispersion of polypropylene fibers. Finally, polypropylene fibers were incorporated into the mix as the third step of the composite preparation process which varies between 0 and 2%. For each mix proportion and curing age (14, 28, and 56 days), three identical cube specimens (70×70×70 mm) were tested to determine compressive strength, and three identical beam specimens (304.8×76.2×12.2 mm) were tested to determine flexural strength. Beam specimens with an overall length of 304.8 mm were prepared using the specified mix proportions and cast in steel molds. After 24 hours, the specimens were demolded and spray cured at a controlled laboratory temperature of 27 ± 2 °C for 14, 28 and 56 days prior to testing. Flexural behavior was evaluated using a three-point bending test under simply supported conditions. The effective support span (L) was maintained at 254 mm using two roller supports. A single concentrated load was applied vertically at the mid-span of the beam through a loading nose. The tests were conducted under displacement-controlled loading at a constant rate of 0.5 mm/min using a calibrated universal testing machine. Mid-span deflection was measured using a linear variable differential transformer (LVDT) mounted at the bottom center of the specimen directly below the loading point to eliminate the influence of support settlement. Load and corresponding deflection data were continuously recorded using the testing machine data acquisition system until specimen failure. The reported compressive and flexural strength values represent the average of three specimens. Table 2 displays the compressive strength of polypropylene fiber reinforced engineered cementitious concrete at 14, 28, and 56 days, while Table 3 provides specifics on the flexural strength values at the same curing ages.

Table 2. Compression strength test.

Polypropylene fiber content in (%)	Dimension		Compression strength (N/mm^2)		
	L (mm)	*B* (mm)	14 days	28 days	56 days
0.00	70	70	23.46	30.20	34.40
1.00	70	70	27.67	36.42	36.55
1.25	70	70	29.97	39.48	41.04
1.50	70	70	31.95	47.95	50.61
1.75	70	70	31.12	46.83	46.44
2.00	70	70	29.93	43.97	43.87

Table 3. Flexural strength test.

Polypropylene fiber content in (%)	Dimension			Flexural strength (N/mm^2)		
	L (mm)	*B* (mm)	*D* (mm)	14 days	28 days	56 days
0.00	304.2	76.2	12.2	03.31	04.64	07.08
1.00	304.2	76.2	12.2	08.36	10.01	12.19
1.25	304.2	76.2	12.2	10.19	12.67	14.80
1.50	304.2	76.2	12.2	13.41	17.50	24.12
1.75	304.2	76.2	12.2	11.83	16.23	17.27
2.00	304.2	76.2	12.2	11.03	15.72	16.72

To enhance the clarity of the experimental methodology, representative photographs illustrating the experimental program are presented in Fig. 1. These include the preparation and mixing of ECC constituents, casting of cube and beam specimens, curing process, compressive strength testing of cube specimens, bending test setup for flexural strength evaluation. The inclusion of these figures provides a clear visual representation of the experimental workflow and testing procedures adopted in the present study.

Fig. 2 illustrates the compressive and flexural strength development of ECC specimens containing various proportions of polypropylene fibers, evaluated at curing ages of 14, 28, and 56 days. The data clearly indicate that a polypropylene fiber content of 1.5% yields the most substantial augmentation in mechanical functionality. At 14 days, the maximum compressive and flexural strengths recorded were 31.95 MPa and 13.41 MPa, respectively. Similarly, at 28 days, specimens with 1.5% PP fiber achieved peak compressive strengths of 47.95 MPa and flexural strength of 17.50 MPa. At 56 days, the trend continued, with the highest strengths reaching 50.61 MPa and 24.12 MPa, respectively. The results, thus, underline the advantage of mixing 1.5% PP fibers with ECC, which has already been indicated as the best ratio for strengthening the compressive and flexural characteristics of the material.

Fig. 1. Experimental program illustrating: (a) ECC mixing and specimen preparation; (b) Casting of cube; (c) Beam specimens; (d) Curing of specimen; (e) Compressive strength testing setup; (f) Bending test setup.

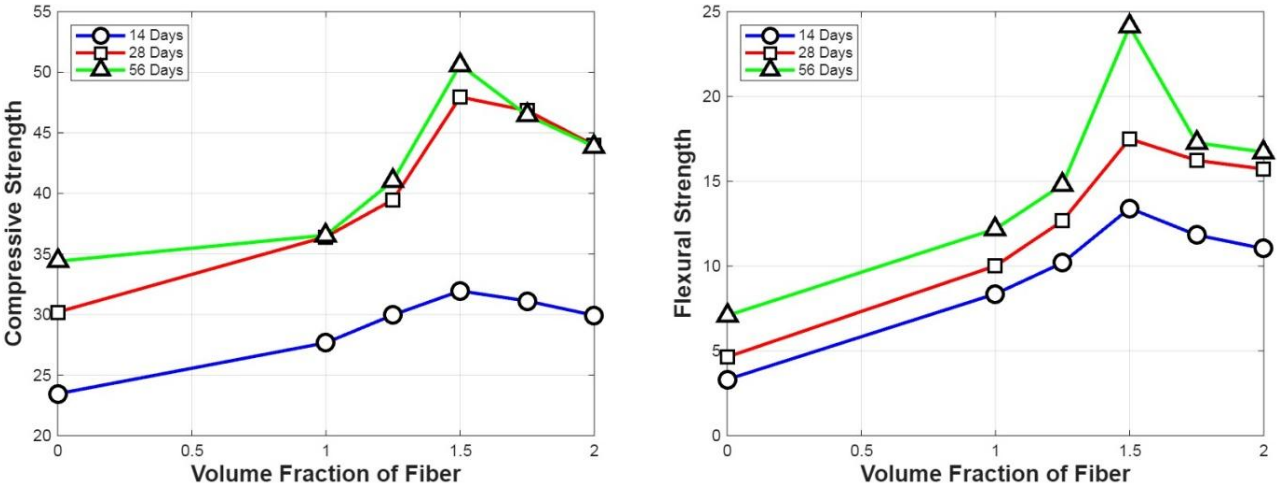

Fig. 2. Compressive and flexural strengths with respect to fiber volume fraction for different curing period.

4. Scanning Electron Microscopy (SEM) Analysis

Scanning electron microscopy (SEM) is an outstanding method that permits the imaging of material surfaces at very high resolution. This technique involves a very fine electron beam that is pointed at the specimen inside the vacuum enclosure. Scanning Electron Microscopy (SEM) analysis was performed using a scanning electron microscope operated at an accelerating voltage of 15 kV, with magnifications ranging from 500x to 5000x. Small fragments obtained from the fractured surfaces of tested specimens were oven-dried, mounted on aluminum stubs, and coated with a thin layer of gold to ensure surface conductivity. The interaction of the electrons with the surface atoms generates various signals, the most common of which being backscattered and secondary electrons, and these signals are the ones used producing the final images. The images produced contain vital information about surface roughness, microstructure, and general morphology of the investigated material represented in Fig. 3.

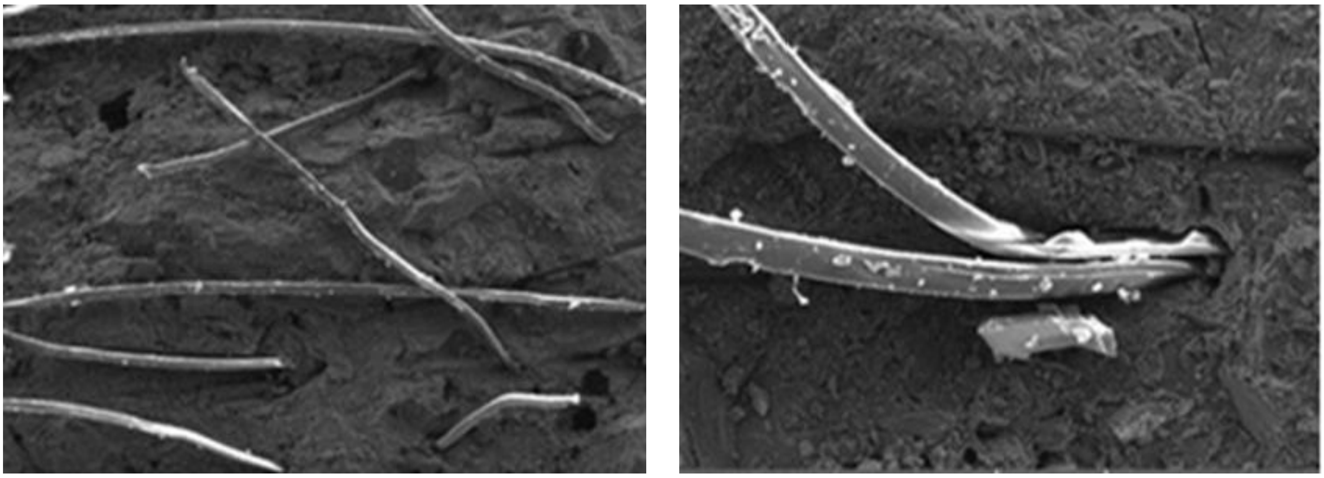

Fig. 3. SEM micrographs of ECC containing 1.5% polypropylene fiber showing fiber–matrix interaction and microstructural morphology (magnification: 2000x; accelerating voltage: 15 kV).

The SEM micrograph very clearly reveals that long and thin polypropylene fibers were embedded in the cement composite. The texture of the surface around the fibers suggests a dense microstructure with a low volume of pores, while the background, which is rough, indicates the presence of sand particles that have been incorporated in the paste. The fibers that are well distributed across the matrix indicate that they are controlling the micro cracks and thus contributing to the overall toughness of the composite. The rough and compact background indicates the existence of hydration products and sand particles, but tiny pores can also be seen. The fibers look to be very well anchored and bonded, and this shows their role in preventing cracks from spreading and thus increasing the overall toughness of the composite.

5. Energy Dispersive X-ray (EDAX) Analysis

Energy X-ray Dispersive Analysis, an also known as EDAX is advanced microscopic analytical method that allows to know the elemental composition of a material. It is usually coupled with electron microscopes like SEM or TEM. Energy Dispersive X-ray (EDAX) analysis was conducted using an attached EDAX detector to determine the elemental composition of the ECC matrix. The analyses were carried out at selected regions of interest to correlate microstructural features with mechanical performance is represented in Fig. 4 and results are shown in Table 4. When the electron beam is concentrated on the specimen, it knocks out an electron from the inner shell, and an electron from the outer shell occupies the site.

The transition of electrons emits an X-ray photon that has an energy corresponding to a particular element. The X-rays are detected and a spectrum is generated by the system, where the peak positions correspond to the types of elements present, and the peak heights indicate their estimated concentrations. EDAX is a non-destructive method that provides both qualitative and quantitative information, therefore, it is very useful for understanding microstructural composition. In ECC, it plays a role in confirming the occurrence and dispersal of materials such as cement, fly ash, and other ingredients that influence the strength and durability traits of the composite.

Table 4. EDAX results of ECC with 1.5% polypropylene fiber.

Element	CO_2	MgO	Al_2O_3	SiO_2	SO_3	K_2O	CaO	Fe_2O_3
Weight (%)	40.37	0.47	3.08	17.61	0.88	0.15	35.23	2.22
Atomic	48.11	0.61	1.58	15.37	0.57	0.08	32.94	0.73

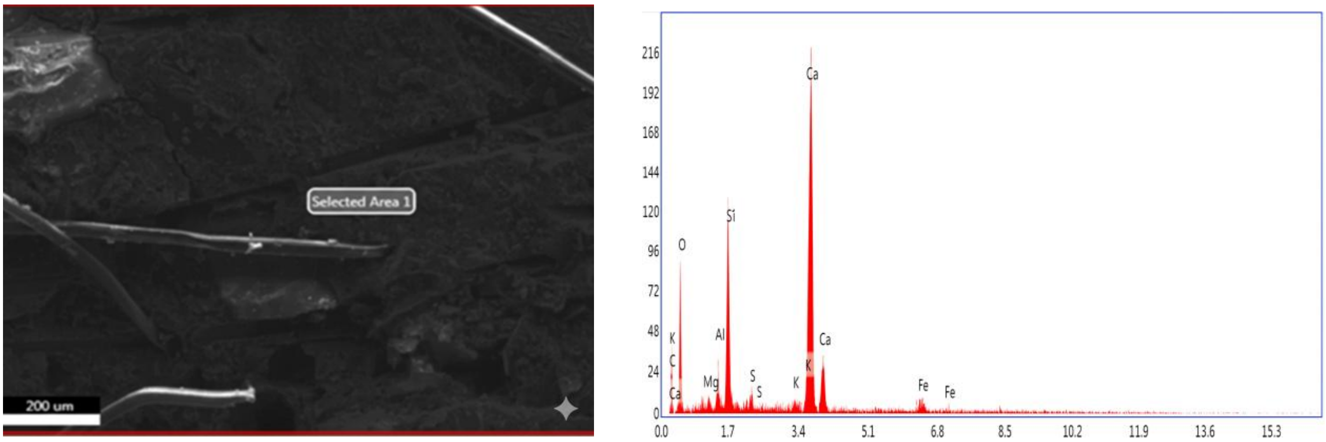

Fig. 4. SEM-EDAX micrograph of ECC with 1.5% polypropylene fiber (Selected Area 1).

6. Artificial Neural Network

Neural networks are computational models guided by the architecture and operation of the human brain. They are designed to manage tasks involving estimation and prediction with multiple input variables. ANN has demonstrated remarkable efficacy in tackling intricate and nonlinear problems. An input layer, one or more Processing layers where learning takes place through weight adjustments, and a prediction layer make up a standard ANN. In accordance with the requirements of the design, the network uses numerous types of activation functions, including tan-sigmoid, log-sigmoid, and ReLU.

As illustrated in Fig. 5(a), the core constituents of a neural network include input values, connection strengths, a summation function, an activation function, and an output. Each neuron receives inputs often derived from external features, which are processed during the training and evaluation phases. These neurons then pass their output as input to the subsequent layer. ANN typically utilizes a feed-forward architecture, where information flows in one direction. Fig. 5(b) illustrates a typical configuration, which corresponds to a multilayer feed-forward neural network. Currently, there is no definitive formula for determining the optimal number of neurons for a specific problem; rather, this is usually identified through empirical testing and iterative refinement.

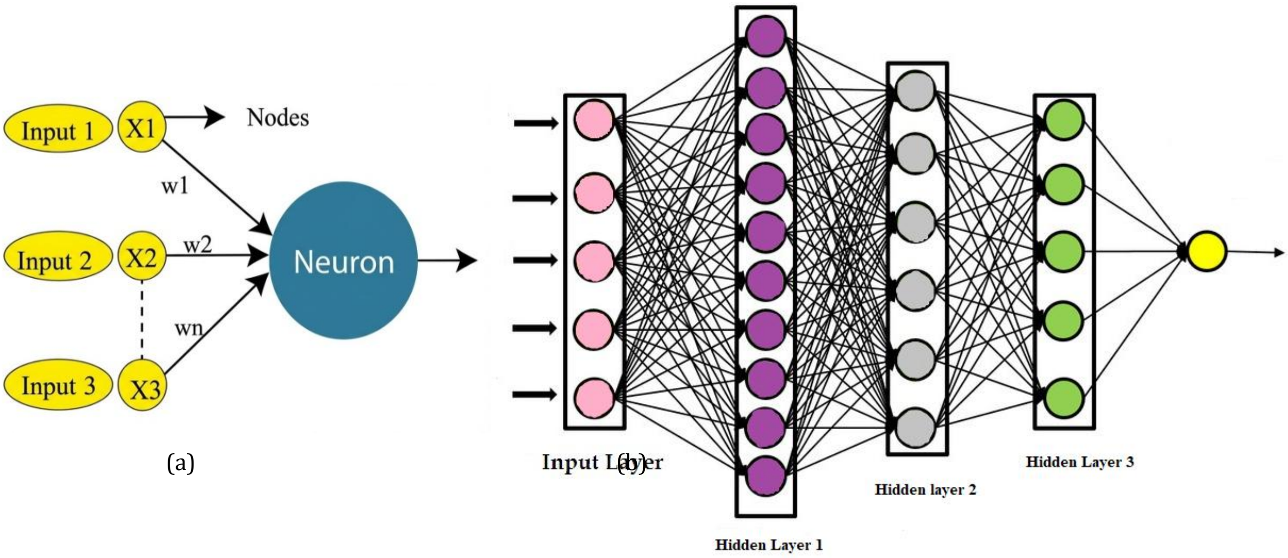

Fig. 5. Structures of (a) Artificial Neuron and (b) Artificial Neural Network.

Since ANN can learn intricate relationships and patterns from data, they are frequently used in prediction tasks across a variety of domains. ANN techniques have been used to predict mechanical properties of concrete based on mix design parameters. Because of their capacity to capture and depict complex and nonlinear connections between the inputs and outputs in the realm of concrete technology, ANN have gained a lot of attention recently.

Prior to ANN training, all input and output variables were normalized using a min–max scaling technique to map the data within a dimensionless range. As a result, the values presented in Table 5 represent normalized inputs rather than raw experimental quantities. For clarity, the original physical ranges of key parameters were as follows: curing age (7, 28 and 56 days), polypropylene fiber volume fraction (0–1.5%), and mechanical strength values expressed in MPa. Data normalization was adopted to enhance model convergence, prevent numerical dominance of higher-magnitude variables, and improve prediction.

Several ANN models have been developed based on mix design parameters to predict the mechanical properties of concrete. Öztaş et al. (2006) highlighted the capability of NN in estimating both compressive strength and slump of high-strength concrete by utilizing various mix design data reported in the literature. Rofooei et al. (2011) utilized an ANN model to predict the vulnerability of conventional reinforced moment-resisting frames and to estimate the associated seismic damage index. Topçu and Saridemir (2008) employed ANN and fuzzy logic approaches to forecast the compressive strength of concrete incorporating high- and low-lime fly ash at curing ages of 7, 28, and 90 days. Mashhadban et al. (2016) looked into the influence of fibers on self-compacting concrete through ANN modeling, relying on experimental datasets. In a different investigation, Belalia Douma et al. (2017) attempted to find the level of the ANN models' accuracy in predicting the properties of fly ash self-compacting concrete in part replacing cement.

7. Database

The decision about how well a deep learning model is to predict the properties of ECC concrete mainly relies on the quality and quantity of the training data provided to the network. This research focuses on cement, fly ash, fine aggregate, and polypropylene fiber content percentages. 105 ECC samples were gathered from the comprehensive literature survey and the experimental setup from past research (Ahmed et al. 2025; Chethan et al. 2015; Marushchak et al. 2023; Ranjith et al. 2017; Saljoughian et al. 2024). The statistical parameters of the collected data are summarized in Table 5.

Table 5. Statistical measures of the data.

	Max.	Min.	Mean	Mode	Median	STD	Skewness	Kurtosis
Cement	1.00	0.80	0.97	1.00	1.00	0.07	–2.19	2.840
Fly ash/cement ratio	1.50	0.00	0.88	1.50	0.80	0.48	–0.22	–1.190
Crush sand/cement ratio	1.00	0.400	0.671	0.80	0.60	0.176	0.011	–0.776
Water/cement ratio	0.86	0.300	0.463	0.42	0.42	0.138	1.20	1.734
Water reducer/cement ratio	0.70	0.002	0.077	0.084	0.07	0.126	3.930	16.576
Volume fraction	7.50	0.000	1.744	2.00	1.500	1.554	2.026	4.972
Tensile strength	6.00	4.00	4.79	4.00	5.00	0.80	0.27	–1.560
Young's modulus	5.00	1.400	3.382	3.80	3.80	1.230	–0.684	–1.096
Length of fiber	120	5.0	10.038	12.0	10.00	2.283	–0.879	–0.358
Compressive strength	86.20	14.25	40.55	29.50	38.70	12.50	0.960	2.160
Flexural strength	28.40	1.98	13.30	18.90	13.25	6.110	0.067	–0.616

8. Model Training and Testing

Data preprocessing is an essential step prior to ANN training, as it enhances the accuracy and reliability of the predictive model. This step has to do with removing duplicate records, dealing with missing data, and applying normalization or standardization techniques to make sure that all the input features are properly scaled. For the neural network to make a correct prediction about the material properties, it has to first learn using a dataset where different ECC mix components such as cement, fly ash, crushed sand, water, high-range water-reducing admixture, volume fraction of polypropylene fibers, tensile strength, Young's modulus, and fiber length are taken as inputs and the resulting mechanical properties, namely compressive and flexural strengths, are treated as outputs. The back propagation algorithm is used to modify the connection weights and minimize the prediction errors during the training phase, which basically is the most critical phase in the formation of an ANN. A multilayer feed-forward neural network with two hidden layers of 22 and 30 neurons each was built and trained for this research using MATLAB. Training and Testing Plots of ANN model for compressive and flexural strength prediction is displayed in Fig. 6.

A total of 105 experimental data points were considered for model development, where 90 samples were used for training and the remaining 15 samples were set aside for evaluating the model performance. To improve learning efficiency, the connection was adjoined with a nonlinear sigmoid activation function. To determine the optimal model, over 500 different neural network configurations were evaluated. The ANN model performance was evaluated using regression-based statistical metrics, including the coefficient of determination (R^2), root mean square error (RMSE), and mean absolute error (MAE). The dataset was randomly divided into training (70%), validation (15%), and testing (15%) subsets to ensure reliable model generalization. Model effectiveness was assessed by comparing predicted and experimental values on the independent testing dataset (Figs. 7 and 8).

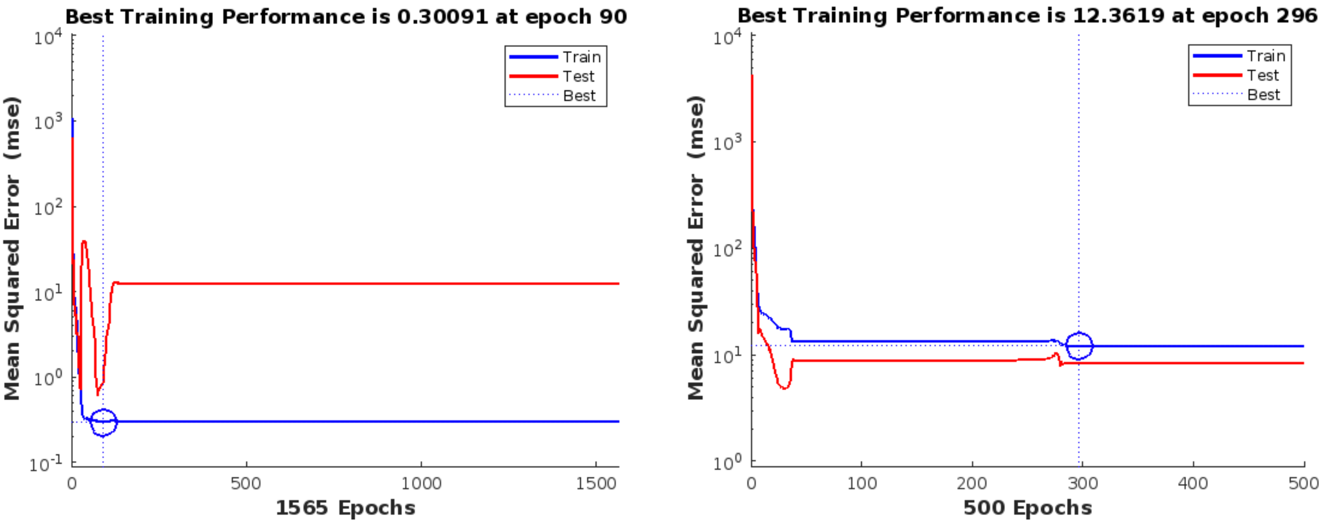

Fig. 6. Training and testing plots of ANN.

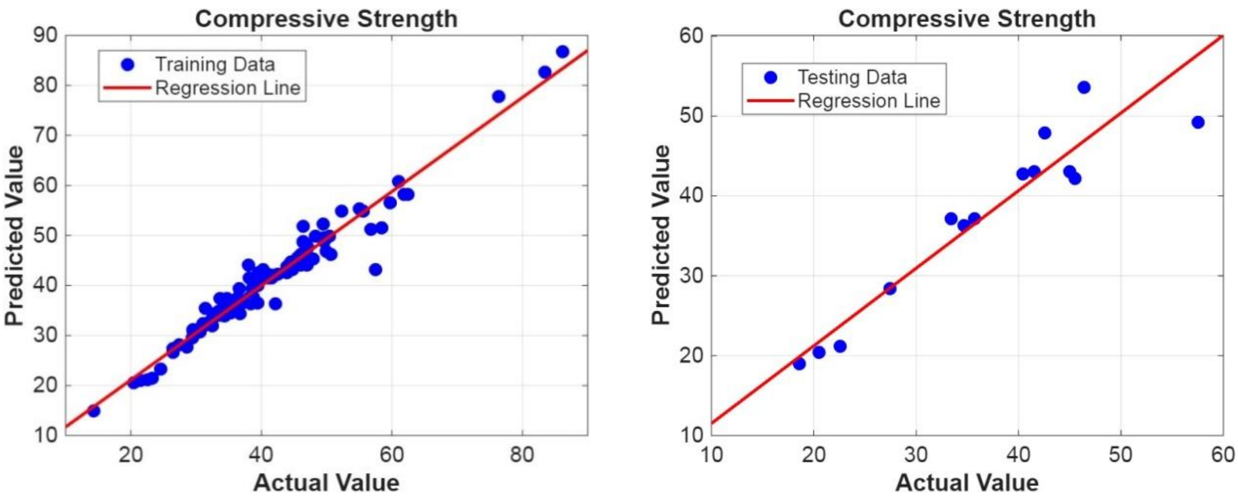

Fig. 7. The assessment of trained and tested data in 28 days compressive strength.

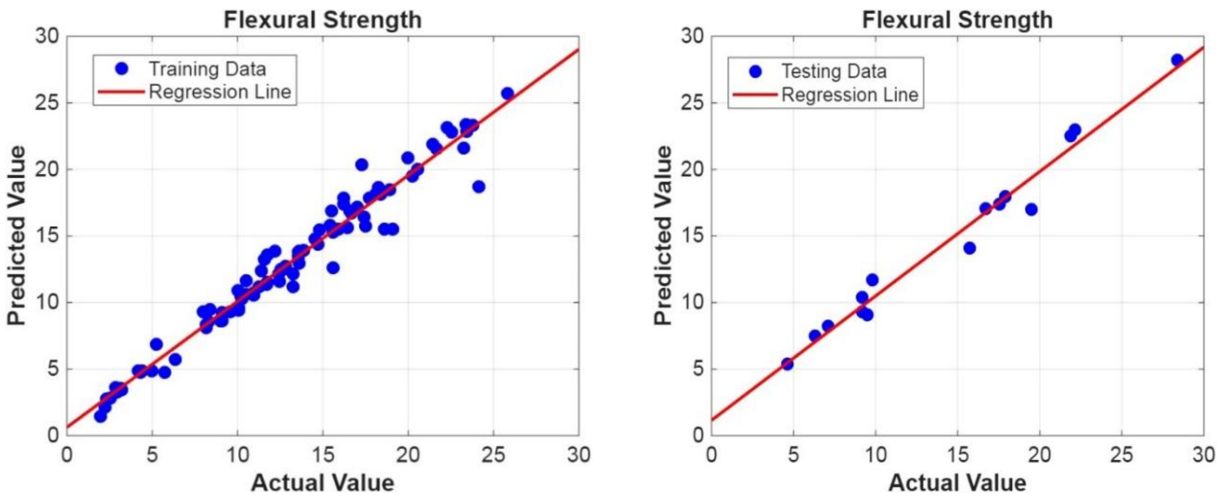

Fig. 8. The assessment of trained and tested data in 28 days flexural strength.

9. Statistical Inference

The accuracy of the predictions was determined using the statistical metrics namely, mean absolute percent error (MAPE), root mean square error (RMSE), and mean absolute error (MAE). The statistical values of RMSE, MAE, and MAPE for the training and testing datasets were displayed in Tables 6 and 7. The highest relative errors for 28-day compressive and flexural strengths during training were recorded as 24.92% and 30.558%, respectively, while the lowest relative errors were only 0.003% and 0.098%. In the testing phase, the maximum relative errors for 28-day compressive and flexural strengths were measured at 15.58% and 19.10%, with the corresponding minimum relative errors being 0.384% and 0.367%.

Table 6. Relative errors of training data.

	Max. relative error (%)	Min. relative error (%)	MAPE (%)	RMSE	MAE	R^2
Compressive strength	24.920	0.0003	4.120	2.675	1.754	0.955
Flexural strength	30.558	0.0980	6.656	1.149	0.735	0.963

Table 7. Relative errors of testing data.

	Max. relative error (%)	Min. relative error (%)	MAPE (%)	RMSE	MAE	R^2
Compressive strength	15.58	0.384	6.409	3.593	2.67556	0.953
Flexural strength	19.10	0.367	8.181	1.119	0.86913	0.975

The histograms in Figs. 9 and 10 show the relative percentage error distribution for the 28 days compressive and flexural strengths. It is worth noting that nearly 70% of the samples were found to have prediction errors not higher than 10%, thus confirming the predicting power of ANN model and reliability in terms of ECC strength parameters. The statistical data demonstrates that, the ANN model has properly learned the relation between input parameters and mechanical properties and it has good generalization ability and high predictive accuracy.

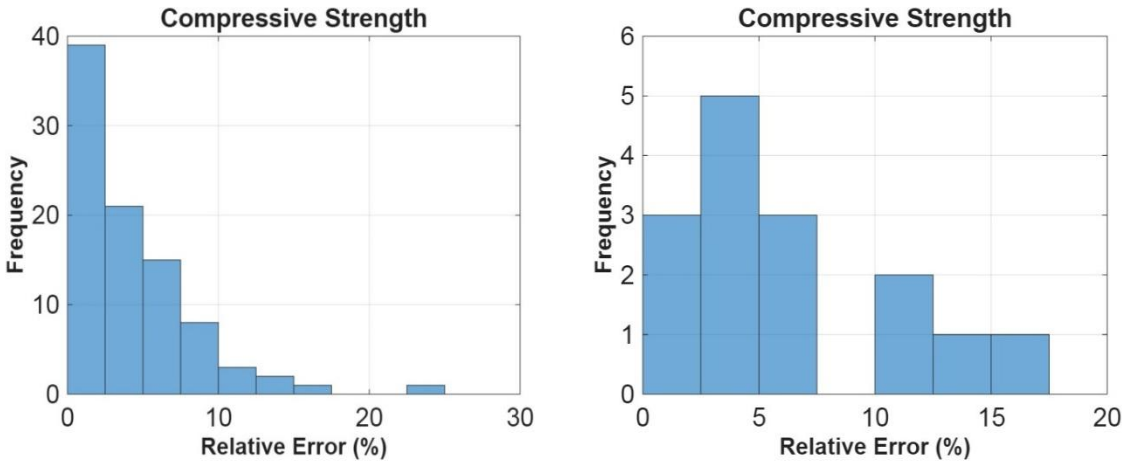

Fig. 9. Histogram of relative error percentage of 28 days compressive strength for training and testing.

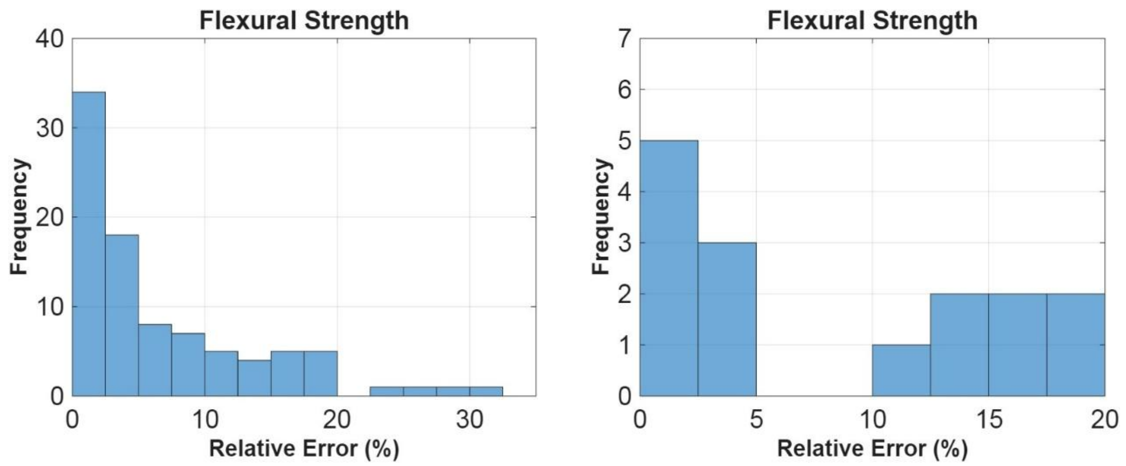

Fig. 10. Histogram of relative error percentage of 28 days flexural strength for training and testing.

10. Results and Discussion

The experimental results demonstrate that the incorporation of polypropylene fibers significantly influences the mechanical performance of engineered cementitious composites. The relationship between compressive strength and polypropylene fiber volume fraction, shown in Fig. 4 indicates that the compressive strength rose slowly but surely with the addition of fiber until optimal fiber content was reached, after which only a slight increase was noted. This pattern suggests that the polypropylene fibers indirectly provide compressive strength by preventing microcracks from forming and spreading instead of by bearing the compressive force. An appreciable increase in flexural strength was observed with increasing polypropylene fiber volume fraction, confirming the effectiveness of fibers under tensile and bending stresses. During three-point bending tests, ECC specimens exhibited multiple fine cracks instead of a single dominant crack, demonstrating the characteristic pseudo strain-hardening behavior of ECC.

The mechanical performance obtained in the present study is consistent with trends reported in the existing ECC literature. Several studies have shown that polypropylene fiber contents in the range of 1.0–2.0% lead to significant improvements in flexural strength and ductility due to effective fiber bridging and multiple microcracking behavior. For instance, ChiaHwan and JianBo (2014) reported optimum PP fiber contents between 1.2% and 1.6%, beyond which fiber agglomeration and workability loss resulted in marginal or reduced strength gains. A similar trend was observed in the present study, where the maximum compressive and flexural strengths were achieved at 1.5% PP fiber content, followed by a slight reduction at higher dosages.

In terms of flexural performance, the 28-day flexural strength of 17.50 MPa obtained in this study at 1.5% fiber content is comparable to the values reported by Marushchak et al. (2023) and Saljoughian et al. (2024) for polypropylene fiber-based ECC systems, confirming the effectiveness of PP fibers in enhancing tensile and bending resistance. The observed multiple fine cracks and stable post-cracking response are also in agreement with the strain-hardening behavior reported in earlier ECC studies.

Regarding predictive modeling, the ANN developed in the present study achieved R^2 values exceeding 0.95 for both compressive and flexural strength prediction, which is comparable to or slightly higher than those reported in recent ANN-based studies on fiber-reinforced and ECC-type composites. For example, Kavya et al. (2022) and Hossain et al. (2024) reported R^2 values in the range of 0.90–0.96 for strength prediction using ANN models. This comparison indicates that the proposed ANN framework provides reliable predictive capability while being specifically tailored to polypropylene fiber-reinforced ECC.

The EDAX analysis of ECC containing 1.5% polypropylene fiber, as presented in Table 4, confirms the presence of major cementitious oxides such as CaO, SiO_2, and Al_2O_3, which play a critical role in hydration reactions and strength development of cement-based materials. Minor oxides such as MgO, SO_3, and K_2O detected in the present study fall within typical ranges reported for cementitious composites and are not considered detrimental at low concentrations. The relatively uniform elemental distribution observed in the polypropylene fiber-reinforced ECC indicates good matrix continuity and compatibility between the fibers and the cementitious phase.

The ANN provide an effective and reliable approach for predicting the compressive and flexural strength of polypropylene fiber-reinforced engineered cementitious composites. The developed multilayer feed-forward model, trained using the back-propagation algorithm, exhibited strong agreement between predicted and experimental strength values for both training and testing datasets. For the training data, the ANN achieved R^2 values of 0.955 and 0.963 for compressive and flexural strength, respectively, with low MAPE values of 4.12% and 6.66%, as summarized in Table 5. In like manner, the R^2 values of 0.953 for compressive strength and 0.975 for flexural strength were obtained for the testing dataset along with MAPE values of 6.41% and 8.18%, respectively in Table 6, which demonstrates great predictive power and excellent generalization performance of the model.

11. Conclusions

According to the data, the addition of 1.5% polypropylene fiber seemed to be the most effective way to improve the mechanical performance of concrete. The dosage offered the highest compressive strength of 31.95 MPa and the highest flexural strength of 13.41 MPa after 14 days of curing, 47.95 MPa and 17.50 MPa after 28 days of curing and 50.61 MPa and 24.12 MPa after 56 days of curing. It can be inferred that polypropylene fiber at a dosage of 1.5% not only enhances the strength of ECC but also serves as a feasible and optimal percentage for mechanical property enhancement.

The microstructural examination strengthened the experimental and modeling results. Scanning electron microscopy uncovered the cementitious matrix to contain polypropylene fibers that had been perfectly embedded, as well as numerous cracks that were very fine but fiber-bridged, thus validating the strain-hardening mechanism typical of ECC. The observed presence of adhered matrix particles on fiber surfaces is a sign of strong fiber-matrix interfacial bonding that leads to better control over cracks and increased ductility. Energy-dispersive X-ray analysis not only verified the existence of pivotal cementitious oxides like CaO, SiO_2, and Al_2O_3 but also revealed a homogeneous elemental distribution in fiber-reinforced specimens, which in turn implies good matrix-fiber compatibility.

The current research provided evidence that Artificial Neural Network is the best choice for the prediction of compressive and flexural strength of polypropylene fiber-reinforced engineered cementitious composites. The multilayer feed-forward ANN constructed and trained by the back-propagation algorithm had almost the same predicted and measured strength values for both the training and testing groups of data. The small prediction inaccuracies suggest that the model has managed to depict the nonlinear connection between the design parameters and the mechanical performance, thus allowing for prompt strength estimation of ECC mixtures that fall within the specified range of the training data.

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Conflict of Interest

The authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this manuscript.

Data Availability

The datasets generated and/or analyzed during the current study are not publicly available but are available from the corresponding author upon reasonable request.

AI Assistance

No AI-based tools were used in the preparation of this manuscript.

Author Contributions

All authors made substantial contributions to the conception and design of the study, acquisition of data, analysis and interpretation of data; drafted or critically revised the manuscript for important intellectual content; and approved the final version to be published.

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