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Soft computing techniques for analysing the mechanical properties of egg shell powder-based concrete

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Abstract:
The construction industry is increasingly focused on sustainability to reduce environmental impact. Researchers are actively exploring alternative materials to replace clinker-based binders. This study specifically investigates the use of eggshell powder (ESP) as a sustainable substitute in construction. Portland slag cement (PSC) is partially replaced by ESP in concrete production for this purpose. To assess the effectiveness of ESP in enhancing binder properties, the study analyses experimental data for compressive and flexural strength. Artificial Neural Network (ANN) modelling is employed for this analysis to predict material performance. The model undergoes training and testing using input data to ensure accuracy and reliability. The success of the study is demonstrated by high R2 values, with 0,9915 for compressive strength and 0,9921 for flexural strength, indicating that the ANN model closely matches actual material performance. Additionally, error analysis confirms the model's remarkable accuracy in predicting real-world results. Furthermore, the research highlights the exceptional potential of the developed ANN model, which can effectively predict the mechanical properties of construction materials containing ESP.

Keywords:
clinker-based; ESP; PSC; ANN; compressive strength; flexural strength

1 Introduction

The production of clinker-based binders (CBBs) and other building materials, particularly cementitious materials (CMs), has a significant impact on the environment [1]. Construction has seen rapid growth [2] due to urbanisation, leading to a substantial increase in the demand for CMs. Construction primarily involves three components: aggregates, cement, and water, combined to manufacture concrete. Cement plays a crucial role in construction [3-5]. Manufacturing CBBs is a highly energy-intensive process that produces large amounts of greenhouse gases, mainly carbon dioxide (CO_2) [6]. The extraction of natural aggregates, another essential component, consumes significant energy and contributes to CO2 emissions. The combined impact of manufacturing concrete has adversely affected the environment and depleted natural resources [7], raising sustainability concerns. To address these environmental challenges and promote eco-friendly construction practices [8, 9], experts have focused on replacing CBBs and aggregates with alternative materials [10, 11]. Progressive efforts have therefore concentrated on exploring various alternative materials [12] to reduce the environmental burden associated with CMs.

Previous studies have already explored and emphasised the potential of alternative aggregate and cement materials [13-15]. The objective is to identify environmentally friendly and economically viable substitutes suitable for widespread adoption. Integrating these alternatives can help the construction industry reduce its environmental impact and conserve natural resources [16,17].

Recycling construction waste materials offers a promising approach to reducing the requirement for fresh aggregates and CBBs, while also addressing environmental issues linked to waste disposal. Waste can be broadly categorised into two types: industrial waste and agricultural waste. Both have been extensively researched as potential substitutes for cement and aggregates. Industrial waste materials such as fly ash, silica fume, slag, and other additives have been found to enhance concrete performance while reducing production costs [18-21]. Similarly, agricultural waste has been investigated as a viable alternative to traditional building materials [22]. Studies have indicated that certain agricultural by-products possess suitable properties as substitutes in CBBs [23]. Utilising agricultural and industrial waste not only diminishes the demand for conventional materials but also aids in sustainable waste management and reduction.

Several researchers have validated the use of agricultural and industrial waste materials for construction purposes [24-27]. This approach is suitable for waste management while promoting environmentally conscious building practices. However, a common challenge associated with utilising these waste materials is their insufficient calcium oxide (CaO) content, which can result in concrete with suboptimal strength [28]. Such issues are addressed using alternative materials, one of which is eggshell (ES), noted for its calcium abundance [29, 30]. In fact, eggshells have been utilised as a calcium source for synthesising calcium phosphates since 1999 [31-37]. The scientific community and later the industry began incorporating eggshells for their calcium content [38].

Eggshell powder (ESP) possesses distinct chemical, physical, and mineralogical properties that distinguish it from traditional CBBs [39], offering innovative applications. A notable study by Hemalatha et al. (2016) [40] showcased the potential of eggshells by using them as a partial replacement for cement alongside high-volume fly ash (HVFA) to enhance concrete strength. Eggshells contain a significant amount of calcium carbonate ($CaCO_3$), extracted from the shells and then incorporated into fly ash cement to expedite hydration [41-43]. Integrating eggshells into CMs serves a dual purpose: repurposing common bio-waste material while enhancing CM performance. The calcium-rich nature [44] of eggshells addresses calcium oxide deficiencies in other waste-based materials, ultimately improving concrete's structural integrity.

The use of prediction models to assess the efficacy of materials and buildings is increasingly popular, aiming to reduce the need for repetitive and time-consuming laboratory trials. These models mainly employ regression-based methods to estimate construction material properties. Notably, machine learning (ML) techniques [45, 46] have emerged as key contributors to the advancement of these models. Artificial neural network methods, in particular, play a significant role in forecasting construction material performance. By analysing vast datasets, these techniques identify patterns and relationships, enabling the creation of accurate and efficient models [19].

Extensive research into the viability of incorporating ESP [47] in the building industry has been undertaken on a large scale despite the absence of formal endorsements within regulatory codes of conduct. However, critical literature studies reveal a noticeable gap concerning the development of comprehensive predictive models to forecast the mechanical properties of ESP concrete [48]. Despite extensive research in concrete technology and materials science, there is a lack of comprehensive investigations focusing on creating precise predictive models tailored to ESP concrete. The current study aims to address this gap by developing a predictive ANN model for determining ESP concrete's compressive and flexural strength. The methodology adopted in this endeavour utilizes Python, enabling researchers to preprocess data, build and train ANN models, and evaluate their performance efficiently. This study signifies a novel approach incorporating advanced computational techniques to enhance understanding and prediction capabilities in ESP concrete research.

In this study, we thoroughly investigate the mechanical properties of concrete incorporating ESP. Our aim is to develop a predictive model for the compressive and flexural strength of ESP-replaced concrete. These two properties are chosen because they play a central role in determining the structural behaviour of concrete members. The researchers develop a machine learning model using input data and predict the output, representing a mechanical property. Error analysis compares the predicted data to experimental results, assessing the model's accuracy. Additionally, the researchers use various model performance parameters to quantitatively measure the effectiveness of the model in predicting concrete properties.

This study focuses on predicting concrete strength sequentially. It encompasses descriptions of the materials and methodology employed and the generation of dataset points through experimental programs. Finally, the study compares the experimental and predicted outputs for both the training and testing phases of the model.

2 Materials, methodology and data generation

The study utilised ESP and PSC as its main materials. Its primary objective is to assess ESP's viability as a partial substitute for conventional cement in construction applications. The ESP (Figure 1) is procured as a ready-made product from INDIAMART. In experimental trials, this prefabricated ESP is used as a partial replacement for PSC. This method simplifies the testing procedure, employing the acquired ESP as an alternative material for PSC.

Figure 1. ESP sample

Table 1 provides a detailed breakdown of the chemical components present in ESP and PSC. This information typically includes the concentrations or percentages of various compounds such as calcium, magnesium, and other elements or compounds found in eggshells. Analysing these compositions is crucial for understanding ESP's potential uses of ESPs, such as construction materials.

Table 1. Chemical composition of eggshell and PSC

Egg shell powder		PSC	
Element/Compound	**Weight** (%)	**Element/Compound**	**Weight** (%)
$CaCO_3$	96,48000	CaO	59,12
S	1,77500	SiO_2	20,41
Mg	0,70000	$Al2O_3$	7,05
P	0,50450	MgO	3,77
Al	0,36000	$Fe2O_3$	3,24
K	0,08390	SO_3	4,15
Sr	0,09585	Na_2O	0,18
Ca – Calcium; CO_3 – Carbonate; S – Sulphur; Mg – Magnesium; P – Phosphorus; Al – Aluminium; K – Potassium; Sr – Strontium; Si- Silica; Fe- Iron; Na- Sodium.			

The scanning electron microscopy (SEM) was conducted on ESP specimens, and the findings are presented at varying magnifications in Figure 2. In this case, it was employed to examine the ESP particles and their characteristics at different scales.

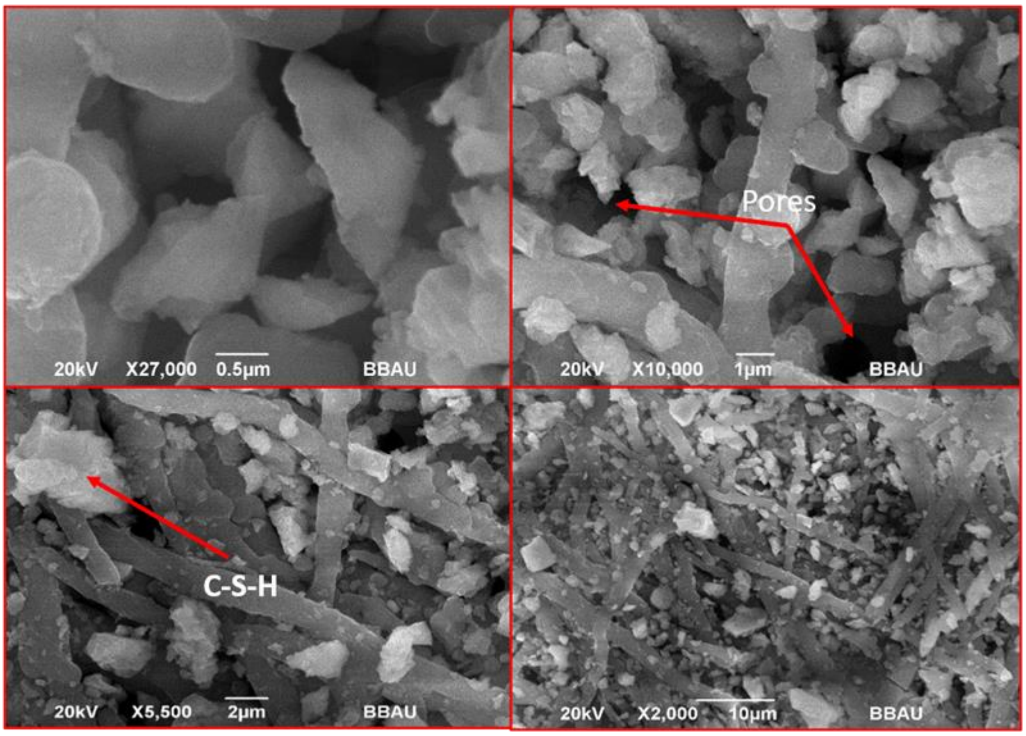


Figure 2. Scanning electron microscopy (SEM) of Eggshell at different magnifications

Figure 2 illustrates the SEM morphology of the ESP, which shows a heterogeneous surface with irregularities and pores at various magnifications. The micrographs show that the microstructures exhibit a distinctive nonuniform size distribution of particles and an irregularly shaped structure. This observation is consistent with the findings of previous study [49, 50]. Additionally, the microstructure revealed ample porosity, which may provide and enhance the contact area for catalysing the reactions. The irregular shape, nonuniform size distribution, and observed porosity of ESP particles may reduce the compressive strength when cement is replaced with ESP [51]. Moreover, an inconsistent morphology can affect the workability of the concrete mixture [52].

The PSC was systematically partially replaced by ESP in increments of 2,5 %, ranging from 0 % to 20 %. Two crucial mechanical tests were performed to assess the influence of ESP on

the compressive and flexural strengths. In the experimental setup, the study involved casting concrete samples designed for compressive and flexural strength tests. Specifically, cubes (150 × 150 × 150 mm) were cast to assess compressive strength, and prism specimens (500 × 100 × 100 mm) were used for flexural strength testing.
A total of 144 cubes and 144 prisms were cast as data points. After casting, the specimens underwent a 24-hour curing period in moulds.
A methodological approach was employed to produce specimens for eggshell concrete. Various components were utilised, including cement, ESP, coarse aggregate, river sand, and a water-binder mix. The process involved adding fluctuating amounts of cement and eggshell powder while maintaining a consistent amount of coarse aggregate, river sand, and an appropriate water-binder mix ratio. This systematic combination is aimed at achieving the desired properties and strengths of the resulting concrete. Table 2 lists the mix proportions, specifically for the creation of eggshell concrete, providing structured guidelines for a singular mix proportion.

Table 2. Mix proportion of ESP concrete

Mix Items	Quantity
binder	460,00 kg
cement	425,50 kg
fine aggregate	736,00 kg
coarse aggregate	1242,00 kg
ESP	7,50 %
water-to-binder ratio	0,35

The data generated through experimental programs is invaluable for machine learning (ML) applications. It is utilised to develop and validate ML models in this context. Specifically, an artificial neural network (ANN) [45, 49] was utilised for this study, integrated within the Python programming interface. The data was normalised and scaled using the standard scalar technique. To ensure the reliability of the ML model, a common practice is to split the available data into two portions: a training set and a testing set. In this case, 70 % of the data was allocated for training the model, with the remaining 30 % reserved for testing its performance.
A feed-forward neural network [46, 48] operates by sequentially processing input data in a forward direction through its layers and neurons without forming cycles in connections. It comprises one input layer, one or more hidden layers, and one output layer. Each neuron is connected to neurons in the subsequent layer by weighted connections. During the feedforward process, input data is propagated through the network, and each neuron computes a weighted sum of its inputs, which is then transformed using an activation function. This output becomes the input for the next layer, and the process repeats until the final output layer is reached. The network is trained through a supervised learning process, adjusting the weights of connections based on the discrepancy between predicted and actual outputs, minimising a defined loss function. This training enables the network to learn complex mappings and make predictions on new, unseen data. A feed-forward ANN has been chosen because it is more suitable for structured data where the relationship between input features is not highly dependent on the order of the data points.
The feedforward neural network architecture used in this study involves an input layer with five neurones representing the features or variables used as inputs to the network. These five inputs are related to the concrete mix characteristics that incorporate ESP and PSC. The input features included variables such as the fraction of PSC and ESP, coarse aggregate (CA), fine aggregate (FA), and water-to-binder ratio (w/b). Figure 3 illustrates the working process of this artificial neural network. Although the explanation is brief, it visually depicts data flow within the network. The input layer with five neurones receives the input values, which are then processed within the hidden layers of the network, although specific details regarding these

layers are not provided in the description section. Ultimately, the network produces two output values: the compressive and flexural strengths.

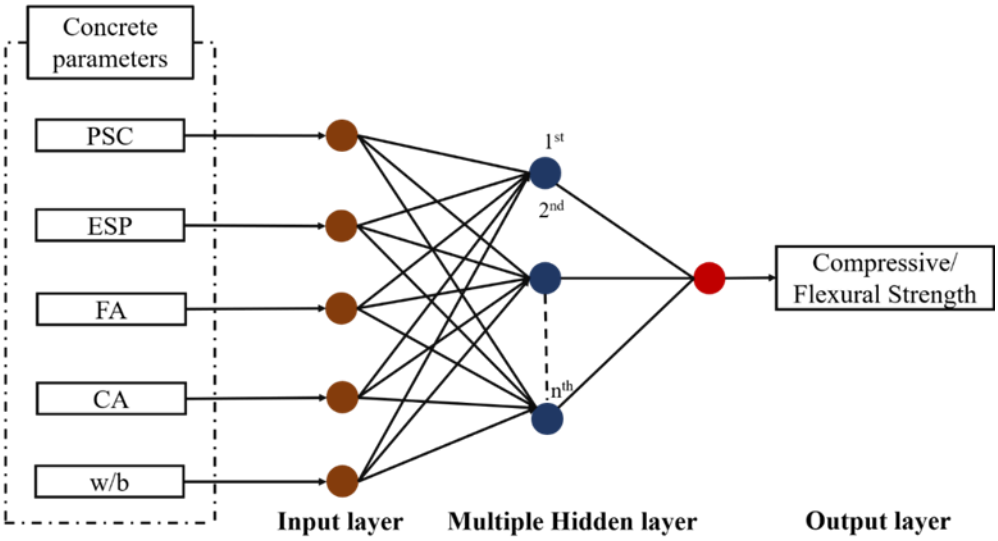


Figure 3. ANN workflow architecture

This separation enables an unbiased assessment of the model's predictive capabilities. Prior to using the data for machine learning (ML), a crucial step involves statistically analysing the dataset. This process entails examining various statistical measures, including mean, standard deviation, minimum, and maximum, to gain insights into the data's characteristics. Such analysis helps identify trends, patterns, and potential outliers, which are essential for making informed decisions during model development. The results of this statistical analysis are then presented in Table 3, providing a structured summary of the key findings.

Table 3. The statical analysis of input and output parameters

Parameter	% ESP	Binder (kg)	CA (kg)	FA (kg)	w/b	CS (MPa)	FS (MPa)
count	144	144	144	144	144	144	144
mean	10	460	1242	736	0,43	26,58	2,45
std.	6,55	0	0	0	0,06	6,89	0,65
min.	0	460	1242	736	0,35	14,71	1,35
25 %	5	460	1242	736	0,38	20,34	1,95
50 %	10	460	1242	736	0,43	27,02	2,37
75 %	15	460	1242	736	0,46	32,29	2,88
max.	20	460	1242	736	0,50	39,21	3,89
CA= Coarse Aggregate; FA= Fine Aggregate; CS & FS stands compressive strength and flexural strength of concrete respectively; Std. = standard deviation.							

Table 3 provides crucial insights into compressive and flexural strength. The analysis shows that the maximum compressive strength recorded is 39,21 MPa, representing the highest observed value, while the minimum is 14,71 MPa, indicating the lowest recorded strength. Likewise, for flexural strength, the maximum is 3,89 MPa, denoting the peak measurement, while the minimum is 1,35 MPa, signifying the lowest recorded value. These maximum and minimum values offer valuable insights into the dataset's variability and range of strengths.

A correlation matrix visually represents statistical correlations, illustrating how various variables interact. The correlation coefficient gauges the strength and direction of the linear relationship between two variables. A correlation coefficient of 1 signifies a perfect positive linear relationship, -1 denotes a perfect negative linear relationship, and 0 indicates no linear relationship. In this context, the focus lies in comprehending how different aspects of concrete composition impact compressive and flexural strengths. These variables may encompass the proportion of cement, ESP, FA, CA, w/b ratio, as well as compressive and flexural strength. Figure 4 presents a correlation matrix illustrating the relationships between compressive and flexural strength and different concrete parameters. The white colour in the matrix denotes a consistent value for coarse and fine aggregates.

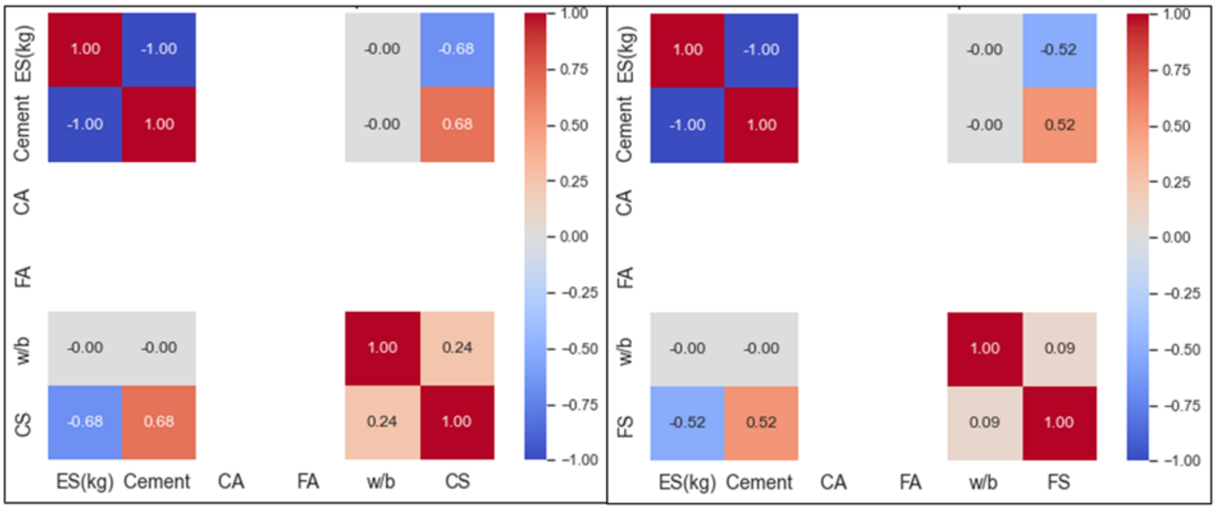


Figure 4. Correlation Matrix for CS and FS

The Root Mean Squared Error (RMSE) is a crucial metric for evaluating the predictive accuracy of models, particularly in forecasting future data points. By calculating the RMSE, analysts gain insights into the average computational deviation between predicted and actual values. Enhanced models typically yield lower RMSE values, indicating superior predictive capabilities. The RMSE is computed using a formula (Eq. 1) that involves mean squared errors (MSE), quantifying the average squared discrepancy between estimated and true values. MSE, derived from squared errors, serves as the central measure of a model's precision (Eq. 2). This statistical tool facilitates the assessment of model performance, providing a standardized approach to evaluate its accuracy. In practice, analysts rely on RMSE to assess a model's reliability in making predictions on unseen data.

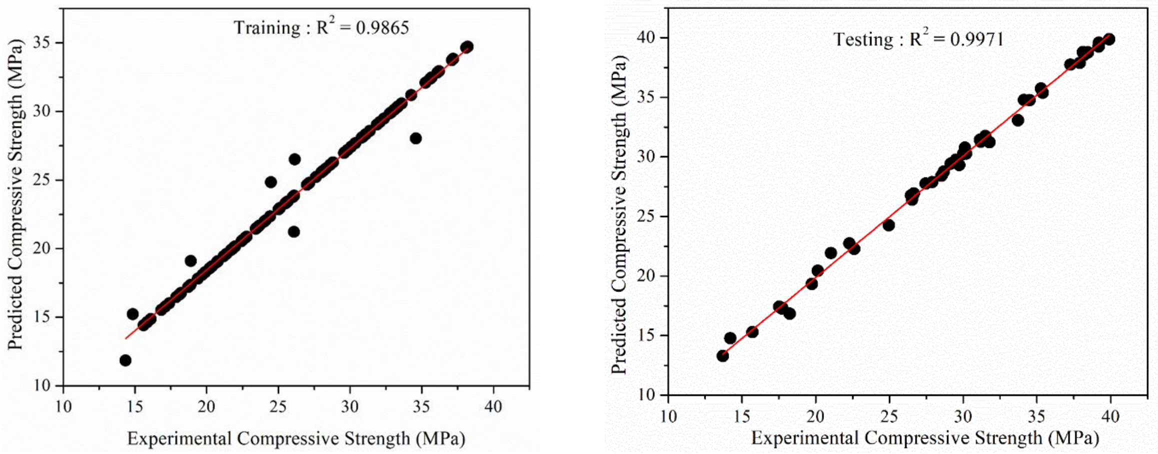
$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}[O_{Ct} - P_{ct}]^2}{N}} \quad (1)$$

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(O_{Ct} - P_{ct})^2 \quad (2)$$

In predictive modelling, *RMSE* and *MSE* are metrics used to assess the accuracy of a model's predictions. Lower *RMSE* and *MSE* values indicate better performance, with values closer to zero suggesting higher accuracy. An *RMSE* or *MSE* value approaching zero indicates that the model's predictions closely match the actual values in the dataset. However, it is important to note that achieving exactly zero is often impractical due to inherent data variability and model limitations. Instead, the objective is to minimise *RMSE* and *MSE* as much as possible, aiming for values significantly smaller than the range of the target variable.

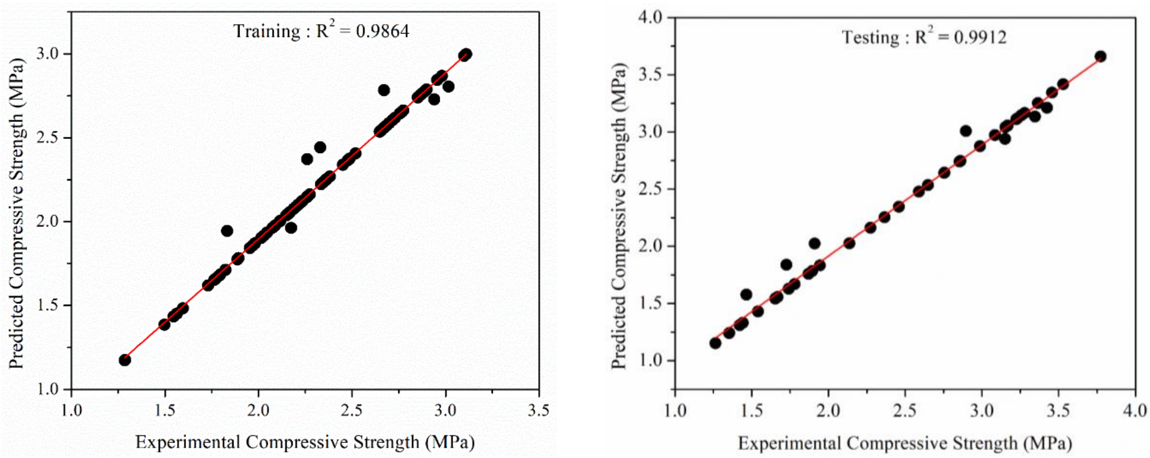
3 Results and discussions

In this section, the study reveals its findings, centred on predictions of compressive and flexural strength. ANN was utilised to formulate and validate models for predicting these strengths. The ANN model for compressive strength underwent meticulous training and testing, as depicted in Figures 5a and 5b. Figure 5a illustrates the training phase, during which the model assimilated information from the dataset. Subsequently, in Figure 5b, the model's efficacy was evaluated through testing. Remarkably, the ANN model for compressive strength demonstrated impressive accuracy. The coefficient of determination (R^2) assesses the model's conformity to the data. The findings reveal an R^2 value of 0,9865 for the training phase, denoting an exceptionally close alignment between the predicted and actual compressive strength values during training. In the testing phase, the R^2 value remains high at 0,9971, indicating the model's exceptional performance when confronted with new data.



(a) (b)

Figure 5. Relation between experimental and predicted compressive strength for (a) training and (b) testing

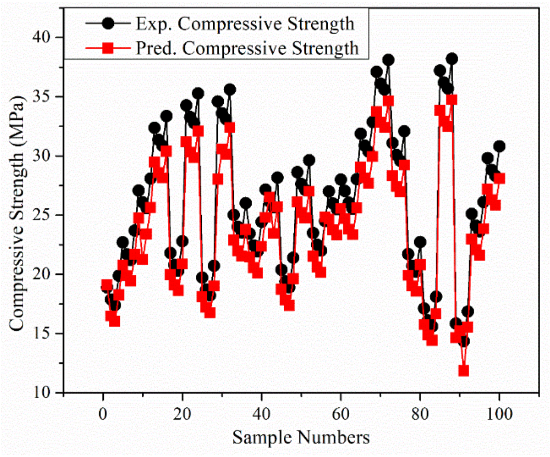


(a) (b)

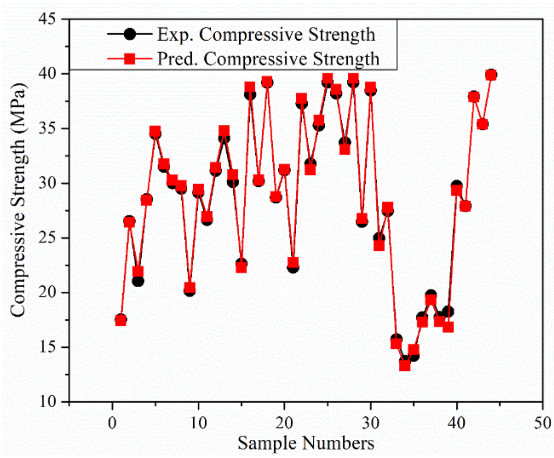
Figure 6. Relation between experimental and predicted flexural strength for (a) training and (b) testing

In the subsequent phase of the study, the researchers shifted their focus to predicting flexural strength. They utilised experimental data on flexural strength as inputs to train and test their ANN model. The ANN model, trained using the flexural strength data, was then evaluated for its performance using the R^2 value, indicating how closely the model's predictions align with the actual flexural strength values. This evaluation process is illustrated in Figures 6(a) and 6(b), depicting the model's behaviour during training and testing. The results of this phase are promising. The ANN model achieved an R^2 value of 0,9864 during the training process, suggesting high accuracy in capturing the relationships within the flexural strength data during the model's learning phase. Moreover, when tested, the model maintained its impressive predictive capability, with an R^2 value of 0,9912.

In Figures 7 and 8 of the study, the researchers present their predictions for both 28-day compressive and flexural strength using ANNs. These predictions are based on data gathered from their experimental programme, specifically the compressive and flexural strength measurements. Figs. 7(a) and 7(b) focus on the 28-day compressive strength predictions. In Figure 7(a), the study illustrates the results of the ANN model during the training phase, where the model learns to make predictions based on the experimental compressive strength data. Figure 7(b) shows the testing phase, where the model's predictive performance is evaluated using new, unseen data. These figures contain visual representations illustrating the comparison between predicted and actual values regarding the 28-day compressive strength values.

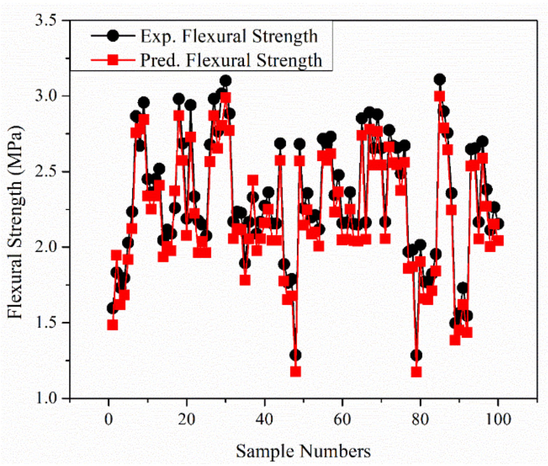


(a)

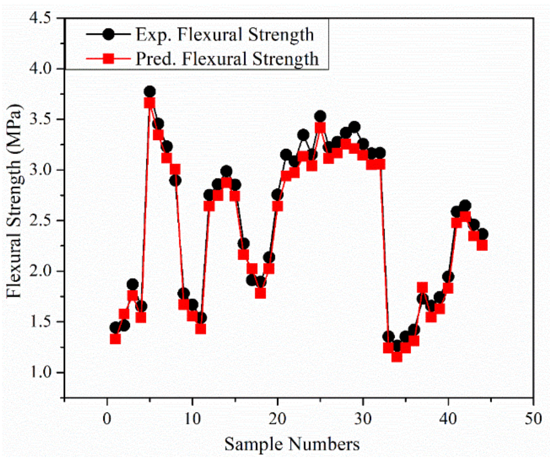


(b)

Figure 7. Comparative study of experimental and predicted compressive strength for (a) training and (b) testing



(a)



(b)

Figure 8. Comparative study of experimental and predicted flexural strength for (a) training and (b) testing

Similarly, Figures 8(a) and 8(b) show the 28-day flexural strength predictions. Figure 8(a) depicts the behaviour of the model during the training process, in which it learns to predict the flexural strength based on the experimental flexural strength data. Figure 8(b) represents the testing phase, showing how well the model predictions aligned with the actual 28-day flexural strength values using data that were not previously encountered. The purpose of these figures is to visually convey the accuracy and performance of the ANN models in predicting the compressive and flexural strengths at the 28-day mark. Table 4 presents information describing the performance evaluation of a model predicting concrete's compressive and flexural strength. This assessment includes both training and testing phases, with results shown in the table. For the compressive strength model, R^2 values for both training and testing are close to 1, indicating a very high level of accuracy in predicting compressive strength. The RMSE for training is 0,7741, representing the average prediction error, and the MAE is 0,4382. For testing, the RMSE is slightly higher at 0,7742, and the MAE is 0,605. These values suggest that the model performs exceptionally well in predicting compressive strength, with low errors in both phases. Similarly, for the flexural strength model, the R^2 values are also close to 1 for both training and testing, indicating high accuracy. The RMSE for training is 0,037, which is very low, and the MAE is 0,0285. In the testing phase, the RMSE is slightly higher at 0,0756, and the MAE is 0,0591. These results suggest that the flexural strength model is also highly accurate, with very low prediction errors.

Table 4. The model performance parameters evaluation for compressive and flexural strength in the training and testing phase

Model performance parameters	Compressive strength		Flexural strength	
	Training	Testing	Training	Testing
R^2	0,9865	0,9971	0,9864	0,9912
RMSE	0,7741	0,7742	0,0370	0,0756
MAE	0,4382	0,6050	0,0285	0,0591

The objective of our study has been successfully achieved by developing a predictive model showing a high R^2 value of 0,9971. This outcome is consistent with the findings of a study conducted by Paruthi et al. (2023) [53], which also utilised ESP in concrete. In their research, they employed ANN to predict concrete strength and achieved an R^2 value of 0,99. These results demonstrate the robustness and effectiveness of ANN models in predicting concrete properties when ESP is incorporated.

The developed predictive model shows promise for future studies seeking to determine concrete strength under similar conditions. However, it is important to acknowledge the inherent limitations in such endeavours. Primarily, these studies require extensive datasets for training and testing the model. The effectiveness and accuracy of the model depend on the quantity and quality of the data points used for training. Therefore, future research should concentrate on collecting comprehensive datasets to improve the reliability and applicability of predictive models in concrete technology that incorporates novel materials like ESP.

Drawing from both recent and past research, it is evident that cement replacement can be executed within the range of 5-15 %. Though this percentage might appear modest, viewed through the lens of waste management, such a practice proves environmentally advantageous. Therefore, ESP can be utilised for less critical tasks.

4 Conclusions

In this study, ESP is used as a partial substitute for PSC in concrete to evaluate its effect on compressive and flexural strength. Experimental programs are carried out to gather data on the performance of these mixtures. ANN is employed to predict the compressive and flexural strengths of concrete mixtures. Rigorous testing of the model is conducted, utilising 30 % of

the collected data to assess its accuracy and reliability. This testing phase entails comparing the model's predictions to the actual test results to ascertain their alignment.
The model's performance is quantitatively assessed using the R^2 value. For compressive and flexural strength, the R^2 values are 0,9971 and 0,9912, respectively, indicating high accuracy in the model's predictions. The study's success is further supported by an error analysis, revealing that the predicted values closely align with the actual values, with a variation of less than 5 %. This suggests that the model effectively captures the behaviour of concrete mixtures with ESP as a partial substitute for PSC. In conclusion, the results of this study suggest that the developed soft computing model is a reliable tool for predicting the compressive and flexural strengths of concrete mixtures containing ESP as a partial replacement for PSC. Our aim was to create a predictive model with high accuracy, which we have achieved with an R^2 exceeding 0,9 and minimal errors.

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