Techno-computing Journal 1(1) 14–26(2025)
https://doi.org/10.71170/tecoj.2025.1.1.14-26
Research Paper

Design of machine learning model for predicting the compressive strength of fabric fiber-reinforced Portland cement

Usman U. Aliyu [1,2*], Mahmud M. Jibril [3], Ismail A. Mahmoud [5], Umar J. Muhammad [5], Jabir Z. Ya'u [5], and Salim I. Malami [6]

[1] *Faculty of Engineering, Department of Civil Engineering, Federal University DutsinMa, Katsina State, Nigeria*
[2] *Civil Engineering Department, Sharda University, Greater Noida, India*
[3] *Faculty of Engineering, Department of Civil Engineering, Kano University of Science and Technology, Wudil, Nigeria*
[4] *Department of Physics Education Faculty of Science and Technology Education, Kano University of Science and Technology Wudil, Nigeria*
[5] *Faculty of Engineering Department of Civil Engineering Bayero University, Kano, Nigeria*
[6] *Institute for Infrastructure & Environment, Heriot-Watt University, Edinburgh, UK*
**Corresponding Author Email: 2023000600.usman@pg.sharda.ac.in, ualiyu12@fudutsinma.edu.ng*

Abstract

Mortar is a combination of cement, sand, and water used in civil engineering works; for joining building blocks, forming structure members, and plastering and masonry. Despite these vast uses, it is linked with structural failures mainly low compressive strength and brittle behavior under tensile stress. To address this, incorporating fabric fiber into the mortar mix has been explored to improve its mechanical performance. This study aims to predict mortar compressive strength a critical mechanical property of a mortar prepared with PC using three soft computing models i.e. feed-forward neural network (FFNN), support vector machine (SVM), and stepwise regression (SWR). The experimental data generated by adding fabric fiber (0%-2%) to the mortar mix and measuring compressive strength at 7, 14, and 28 days of curing age were used to train and test these models. The results revealed that SWR outperformed FFNN and SVM with a training and testing accuracy of 99.97% and 99.67% respectively. The results underscore the potential of advanced modeling techniques like SWR for enhancing mortar performance for the development of more reliable and durable construction materials for sustainable construction through the reuse of textile waste.

Keywords: Artificial Intelligence, Mortar, Compressive Strength, Prediction, Fabric Fiber

1. Introduction

The construction industry has continued to rely on mortar as one of the most widely employed composite materials used in building and restoration constructions. Mortar primarily consists of cement, sand, and water and is crucial in building structures, plastering, and masonry construction. Despite its importance, Mortar is still linked with structural failures, mainly low compressive strength, and brittle behavior under tensile stress [1]. Over the years, fiber reinforcement has become a practical approach to enhance the mechanical characteristics of mortar, and it modifies cracking behavior and brittleness problems [2]. Some of the reinforced fibers commonly used in construction include synthetic fibers, fiberglass, steel, and natural fibers, which all can enhance the characteristics of mortar [3]. Over the recent decades, awareness of products' environmental impacts has directed focus towards the recycling of textile fibers, which provides not only environmental advantages but also architectural

(Received 16 Nov 2024; revised 25 Nov 2025; accepted 28 Nov 2025; first published online 20 March 2025);

advantages when the fibers are integrated into construction materials. Natural fibers are highly available and have the least negative effects on the environment and are preferable for enhancing brittle construction materials like mortar [4]. Moreover, considering the contribution to waste minimization and carbon footprint reduction, recycled textile fibers can also be included in the mortar products utilized in construction projects. Textile fiber waste was classified into three types: production waste, pre-consumer waste, and post-consumer waste, with post-consumer waste contributing the most significant waste stream [5]. Textile waste is either disposed of by landfilling, incineration, or converted to energy; all these methods pollute the environment by emitting methane and carbon dioxide, resulting in soil, air, and water pollution [6] [7].

Population growth and rising living standards have led to a rapid increase in fiber production and fiber waste. Though attempts have been made to recycle fibers for various applications, a large percentage of fiber waste is still dumped in municipal landfills due to problems associated with collection and classification [8] [9]. This problem has been worsened by fast fashion and increased textile production, highlighting the importance of a circular economy that focuses on upcycling to increase the value of products in the recycling process [10]. On the other hand, [11] emphasized that materials with lightweight, flexible, and corrosion resistances, such as biopolymer insulators and composites, offer significant advantages and are increasingly gaining attention. Thus, these materials produced from recycled fiber may be sustainable products for use in construction-related industries. Incorporating textile fiber reinforcement materials enhances mortar strength, durability, flexibility, and thermal insulation compared to conventional methods. Reusing fibers in construction is crucial due to mechanical properties and durability enhancement [12]. It also increases the ability to mitigate processes i.e. shrinkage, expansion, and others that cause crack formation [4] and overall durability [13]. Studies such as [14] employed recycled glass fibers and [15] on reinforced fabric for concrete panels. [16] Show mechanical enhancements by utilizing plastic waste. [17] identified acrylic fiber as comparable to polypropylene fiber and [18] established strength advances with polypropylene/polyethylene PP/PE blends. Similarly, cellulose fibers [19] and recycled nylon from fishing nets [20] also proved efficient, while [21] confirmed the uses of natural hemp fibers for lime-based mortars.

The use of artificial intelligence AI models for flexural strength prediction is important as it helps to estimate the optimal fiber compositions to yield maximum mechanical performance. Prior work has shown the potential of AI in predicting material properties with great precision, even in nonlinear systems [22]. Considering these developments, this research presents a novel application of AI models to evaluate the influence of fabric fiber on mortar compressive strength, highlighting the potential for sustainable construction through the reuse of textile waste. The research aims to leverage AI techniques to predict the effects of fabric fiber on the compressive strength of a mortar made with Portland cement (PC). AI models, including Artificial Neural Networks (ANN), Support Vector Machine (SVM), and Stepwise Wise Regression (SWR), are employed to assess how fabric fiber influences the mechanical performance of mortar. The discoveries from this study will give helpful information concerning the viability of reusing textile fiber in construction and the improvements that can be made to mortar by utilizing green materials in response to sustainable development and reduction of waste.

2. Material and Methods

2.1 Materials

This chapter discusses the material used in this research work and provides details of various tests to investigate the properties of cement mortar reinforced with fabric fiber. The cement used for the experiment was Grade 42.5R, and natural sand obtained from the river was used. Ordinary tap water was used throughout the experiment, with a water-cement ratio of 1:2 as specified by BS158. The fiber used in the experiment was a textile fiber containing a percentage of cotton content obtained from fashion design waste. The fabrics were shredded into pieces with an average fiber length of 6cm, a depth of 0.5 mm, and a density of 52.4 Kg/m^2. The fiber was added to the mortar mix as a percentage of the cement weight.

2.2 Methods

2.2.1 Preliminary Tests on Samples

Preliminary tests were conducted to determine the properties of the materials to be used. The following tests were performed on the cement: specific gravity, fineness, and compressive strength. For the fine aggregates, tests included the particle size distribution, specific gravity, and clay and silt content, while consistency, soundness, and setting time were performed on the aggregates. The particle size distribution of the sand ranged from 0.08 mm to 2.0mm per EN 196-1. The cement to be tested was stored in sealed, air-tight containers made from material that does not react with cement, and the water used for the research was free from salt and other impurities.

2.2.2 Sample Preparation

The mortar used for this experiment has a mix ratio of 1:3 per BS158. The dry mortar was initially prepared by mixing one part of cement with three parts of sand, and the components were thoroughly mixed. Fabric fiber was added at varying mix ratios of 0%, 0.5%, 1.0%, and 2.0%. After thoroughly mixing the constituents, water was added and mixed to produce the cement mortar. Each batch of three test specimens was mixed separately and consisted of 450 ± 2g of cement, 1350 ± 5g of sand, and 225 ± 1g of water, in which the specimen was molded immediately after the preparation of the mortar. During molding, the excess mortar was struck off with the metal straightedge held almost vertically and moved slowly with a transverse sawing motion. The specimens were smoothed using the same straightedge held nearly flat, and the molds were then marked to identify the specimens. The specimen was then cured by placing the molds on a horizontal base in the moist air room for 24 hours. Afterward, the specimens were demolded, marked with water resistance ink, and submerged horizontally. The molds were kept apart to allow free access to water on all six sides of each specimen, with space between the specimens and a depth above the upper faces of at least 5mm. Before testing, each specimen was removed from the water and allowed to sit for about 15 minutes. before the test was carried out. A total of 45 cubes were cast. Nine samples were cast for each fiber replacement level to ensure the accuracy of the results, enabling analysis of the different levels of fiber replacement. Prismatic test specimens dimensioned 40 mm x 40 mm x 160mm were used in determining both Compressive stress and flexural strength. At the specified age, the specimens were removed from wet storage, broken in flexure into two halves, and each half was tested for compressive strength.

2.2.3 Flexural Strength Test

The prism was placed in the testing machine (see Figure 1) with one side face on the supporting rollers with its longitudinal axis normal to the supports. The distance between the supports is 100 mm ±0.5 mm. The load was applied vertically using the loading roller to the opposite side face of the prism and increased smoothly at a rate of 50 ±10 N/s until fracture. The flexural strength R_f was calculated using the relation:

$$R_f = \frac{1.5 \times Ff \times l}{b3} \qquad (1)$$

R_f is the flexural strength in megapascals; b is the side of the square section of the prism in millimeters; Ff is the load applied to the middle of the prism at fracture in newtons; l is the distance between the supports in millimeters.

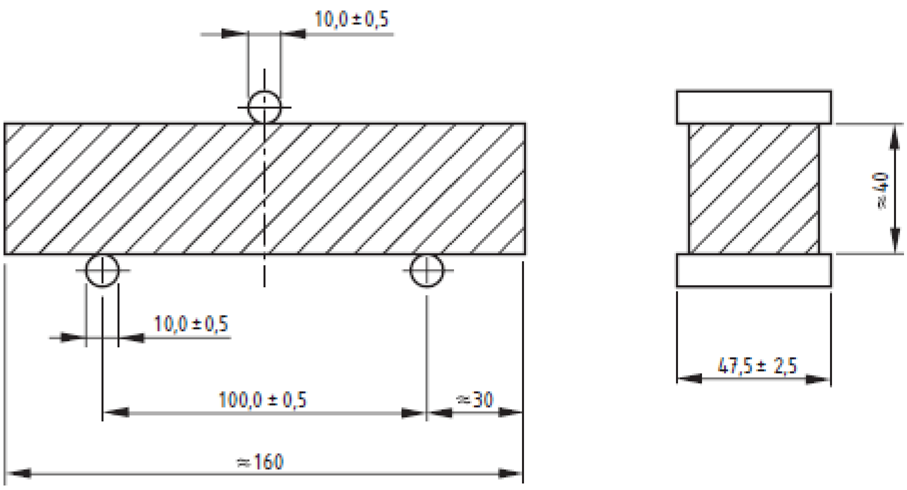

Figure 1: *Mortar prism (40mm × 40mm × 160mm)*

2.2.4 Compressive Strength

The prism halves (after the test of flexural strength) are tested in compression, and the prism halves are laterally centered on the auxiliary platens of hard steel, which exactly determines the compressive area (because the prism halves have an irregular form). The platens size is 40 mm x 40 mm and 10 mm thick per EN 196-1. While loading, the relative attitude of the upper and lower platens remained fixed, and the resultant forces passed through the center of the specimen. The load increased smoothly at the rate of 2400 $\pm$200 N/s over the entire load application until failure. The Compressive strength was calculated from the relation:

$$Rc = \frac{Fc}{1600} \tag{2}$$

where *Rc* is compressive strength (MPa), *Fc* is the maximum load at fracture (N), and 1600 is the area of the platens (mm^2). The test result was defined as the arithmetic mean of the six compressive strength determinations made on a set of three prisms. If any result among the six determinations varies by more than $\pm$It was discarded 10 % from the mean, and the mean of the five remaining results was calculated. If any further result within these five determinations varied by more than $\pm$10 % from their mean, the results test was discarded.

2.3 Model Building

2.3.1 Artificial Neural Network (ANN)

ANN is a computational model that imitates how the human brain processes information. It consists of interconnected nodes, called neurons, organized into layers, which include an input layer, hidden layers, and an output layer [23], as in Figure 2. The neurons in each layer are connected to neurons in the subsequent layer over weighted links. Throughout the forward, during which the network is trained, the input data is used to pass via all the layers, where each connection has an associated weight and bias. However, the neurons combine the input values with these weights and biases and then apply an activation function to introduce non-linearity, allowing the model to learn from complex patterns [24]. ANN is meant to reveal patterns, learn from the data, and make excellent estimations. They are used in different applications that involve the classification of images and speech recognition. The information generated by the ANN is passed to the next layer after being processed by the first layer [25].

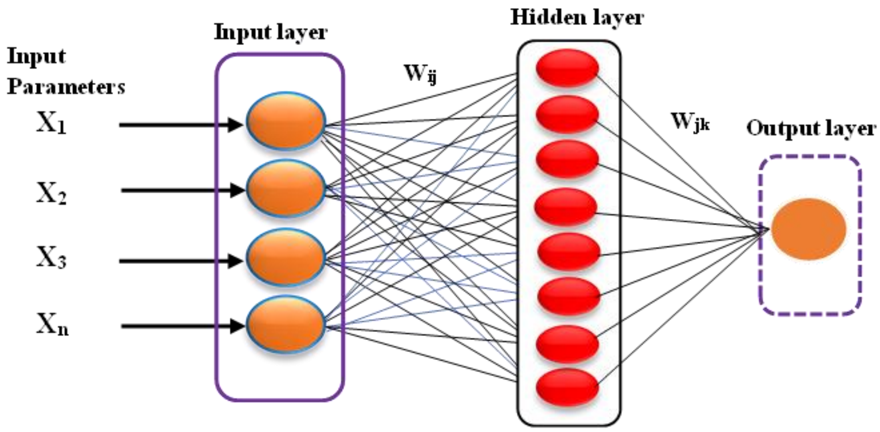

Figure 2: *ANN model structure*

2.3.2 Support Vector Regression (SVR)

SVM is a classification technique Vapnik uses to solve nonlinear problems. SVR is a generalization of SVM that effectively solves any problem concerning regression with a multi-dimensional landscape [26]. However, SVR is among the supervised ML algorithms that predict distinct ideals. The main idea of the SVR is to look for a regression plane in which the actual distance of all points of the data set will be minimized (Figure 3). SVM has robustness outliers with excellent performance and the ability to learn from complex patterns [27]. SVR is an application of SVM in any problem concerning regression. Related to GPR, ANN can take care of nonlinear regression issues more often with the advantage of getting better analysis in different fields. Yet, the SVM model gives precise estimation strength and is easy to put into work rather than optimal results. SVM accepts the main concept of the enticement zone, to which a margin is distinct to take care of the estimation point. The main application of the regression model is called SVR. The regression analysis constructs a hyperplane in the higher space such that the distance from all data points to the hyperplane is minimized, thereby improving the accuracy of predictions for the validation set [28].

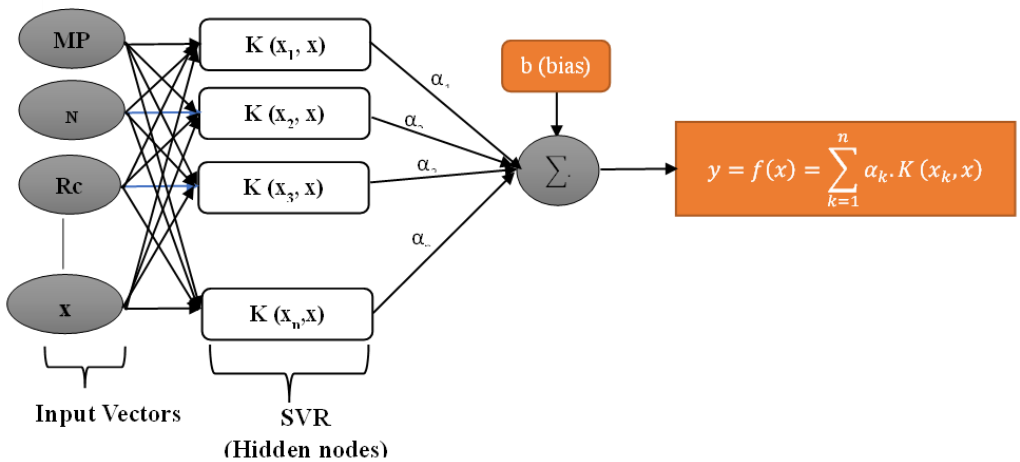

Figure 3: *SVR model structure*

2.3.3 Stepwise Linear Regression (SWR)

The SWR Model is not a single method but a multiple regression analysis technique. SWR is one of the most reliable statistical and mathematical techniques in the research domain, and it is used to sort out and analyze dependencies quantitatively among dependent and independent variables. Regression methods are used to study the interdependence of multiple variables. SWR is used to reveal the ideal or most appropriate regression model to study the interdependence of variables with more insight. SWR can mix and delete one variable at a time, which is the most favorable technique. The SWR independent variable adds the regression equations one at a time based on their influence on the dependent variables. SWR minimizes the dependent variables by using two procedures: advancing and backward algorithms [29]. SWR is used to remove initial regression models based on their statistical relevance in explaining the response variables in many steps. However, it can take care of nonlinear functions of the main features. SWR is a technique used to contract a model by adding or eliminating interpreter variables under the state [30].

2.4 Model Development

The study utilized FFNN, SVM, and the SWR model. All these models were created in MATLAB. In data-driven models, the main goal is to fit the model to the provided data, using relevant indicators to ensure accurate predictions on unseen data sets [31]. Overfitting causes significant ML issues in training and testing performance. To overcome this problem, k-fold cross-validation was performed. In this approach, the data was split into two transitions, i.e., training and testing. The process is advantageous as a result of validation and training sets are nonaligned in each iteration [32], [33], this provides a solid foundation for optimizing model performance. The data in this research was divided into 70% for training and 30% for testing using 10-fold cross-validation. A conventional sensitivity analysis was conducted with a correlation matrix to identify highly influential and suitable predictor combinations with the target variable. This matrix reveals the attribute of the linear combinations among the variables and helps to develop model combinations. The input and the target variables were normalized using Equation 1 before the values employed AI-based models.

$$X_i = \left(\frac{X_i - X_{min}}{X_{max} - X_{min}}\right) \quad (3)$$

2.5 Criteria for Evaluating Performance Predictions

Using the collected data, the results of the analyzed methodologies can be compared with the expected outcomes. To assess model performance, the coefficient of determination (R^2), the mean squared error (MSE), and the root mean squared error (RMSE) were applied in this study. Two accuracy measures are used which are R^2, which indicates the percentage of total variance that the model accounts for, and RMSE, which measures the remaining unseen variance that the model cannot account for [34] [35] [36]. The data in this research was divided into 70% for training and 30% for testing.

$$MSE = \frac{1}{n}\sum_{i=1}^{N}(X_{P,i} - X_{A,i})^2 \quad (4)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{N}(X_{P,i} - X_{A,i})^2} \quad (5)$$

$$\text{R2} = 1 - \left[\frac{\sum_{i=1}^{n}(X_{P,i} - X_{A,i})^2}{\sum_{i=1}^{n}(X_{A,i} - X'_{A,i})^2}\right] \quad (6)$$

$$\text{R} = \sqrt{1 - \left[\frac{\sum_{i=1}^{n}(X_{P,i} - X_{A,i})^2}{\sum_{i=1}^{n}(X_{A,i} - X'_{A,i})^2}\right]} \quad (7)$$

Whereas; $X_{A,i}$ donates the actual data values, $X'_{A,i}$ stands for an average rate of the data and $X_{P,i}$ stands for the predicted values for n data input.

3. Results and Discussion

3.1 Experimental Results

Figure 4 illustrates the mean compressive strength (MPa) of the mortar samples with distinct percentages of fiber used (0%, 0.5%, 1%, 1.5%, and 2%) at the curing times of 7, 14, and 28 days. As shown, the compressive strength increases with time and has the highest magnitude at 28 days for all percentages of fibers. Plain mortar with no added fiber has consistent values rising to 6 MPa at 28 days. The mix with a fiber content of 0.5% and 1 % has comparable strength to the plain mix, and an increase in fiber percentage leads to a decrease in compressive strength at all tested intervals for 1.5 % and 2 % fiber contents. Significantly, 0.5% fiber performs slightly better in 14 days, while it gives poor results at 7 and 28 days compared to the plain sample. The optimal balance seems to be at 1% fiber, as it provides good compressive strength without significantly weakening the mortar. At 1.5% and 2%, strength reduction could be attributed to inadequate bonding or barriers that may interrupt the flow of the cement matrix, thereby reducing compactness. Whereas the literature affirms that fibers commonly contribute to tensile strength and crack resistance, they may also reduce compressive strength. Therefore, it is suggested that the fiber content should be limited to 1% for applications where compressive strength improvement is required. Higher fiber percentages, on the other hand, may be desirable where crack resistance or flexibility is of greater importance than compressive strength.

3.2 AI Prediction-Based Results

The input and the target variables were normalized using Equation 3 before the values employed AI-based models. The normalization range between 0 and 1 was adopted since certain data have high values and can yield wrong results in modeling [37]. The main aim of normalization is to reduce redundancy and to guarantee that all data is scaled equally [38]. As such, the comprehensive quality and standardization of the data are maintained. Considering the correlation results in Figure 6, model one includes two input variables: normal load and flexural load. Flexural strength and mortar age were added to develop the second model, resulting in four input variables. whereas fiber content and density were added to create the inputs for the third model, the compressive strength was predicted as the target variable. As illustrated in Figure 5, the significant variables that are stationary and have a Probability below 0.05 ($P<0.05$) demonstrate a strong linear correlation [39]. Furthermore, the negative correlation values indicate an inverse relationship among the variables [40]. The correlation matrix (Figure 5) shows the central cross relations between the model input and output properties. The significant variables have a Probability below 0.05 ($P<0.05$), indicating a strong linear correlation, and the negative correlation values indicate an inverse relationship among the variables. As shown in Figure 5, compressive strength depends on normal load (0.9992) and moderately depends on flexural strength and flexural load (0.7505 and 0.7484, respectively). But fiber content reduces both the compressive and flexural strength, i.e., (-0.6709) and (-0.4533), respectively. Hence, it suggests that higher fiber content weakens mechanical strength. On the other hand, the analysis indicates moderate effects of curing age in compressive strength ($r=0.4795$) and normal load ($r=0.4682$) but shows weaker correlations with the remaining parameters. Hence, optimizing fiber content is essential for balancing strength and durability in mortar.

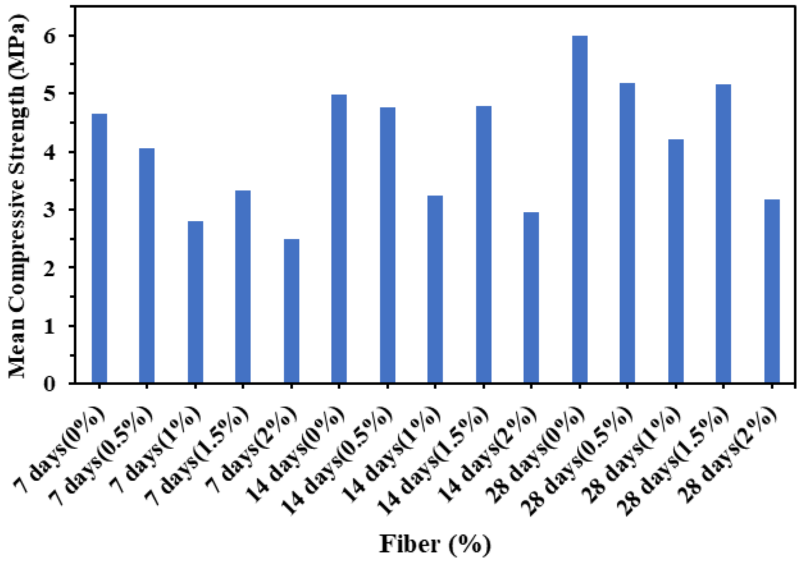

Figure 4: *Mortar compressive strength development at various percentages*

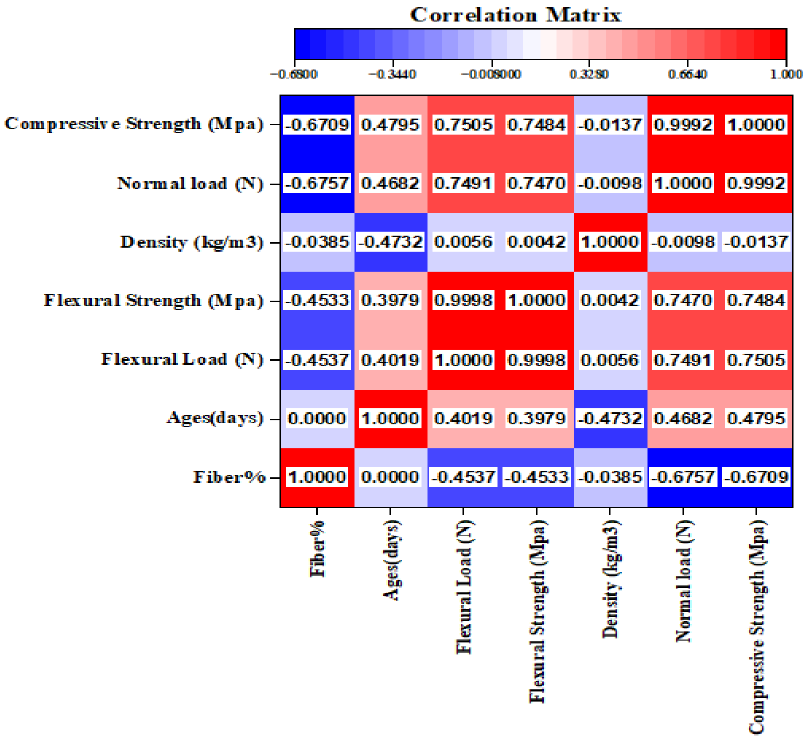

Figure 5: *Correlation Matrix of Prediction Parameters*

Table 1: *Performance Metrics of FNN, SVM, AND SWR Models*

Models	Training Phase				Testing Phase			
	R2	MSE	R	RMSE	R2	MSE	R	RMSE
FFNN-M1	0.9858	0.0011	0.9928	0.03320	0.99226	0.00043	0.99612	0.0207
FFNN-M2	0.9990	7.36E-05	0.9995	0.00857	0.99044	0.00053	0.99521	0.0230
FFNN-M3	0.9888	0.0008	0.9944	0.02944	0.98621	0.00076	0.99308	0.0276
SVM-M1	0.9946	0.00042	0.9973	0.02049	0.99226	0.00043	0.99612	0.0207

SVM-M2	0.9948	0.00040	0.9974	0.02007	0.993	0.00038	0.99649	0.0197
SVM-M3	0.9935	0.00049	0.9967	0.02234	0.99035	0.00053	0.99516	0.0231
SWR-M1	0.9997	2.03E-05	0.9998	0.00450	0.99363	0.00035	0.99681	0.0188
SWR-M2	**0.9995**	**3.26E-5**	**0.9997**	**0.00571**	**0.99694**	**0.00017**	**0.99847**	**0.0130**
SWR-M3	0.9992	3.23E-05	0.9995	0.00558	0.99690	0.00015	0.99844	0.0122

Table 1 presents the performance comparison of several FFNN, SVM, and SWR models for predictive analysis of the cement mortar compressive strength containing fabric fiber made with PC. Through the training and testing phases, all the models showed precision in predicting the impacts of the fiber content on compressive strength determination. According to predictor performance analyses, SWR models yield R2 values of 0.9997 and 0.9969 in the training set of SWR-M1 and testing set of SWR-M2, respectively, indicating the models' predictive capability between the variables. SVM models also show good performance, with SVM-M2 having an R2 of 0.993, showing that the models have good predictive performance. Compared to other models, the FFNN models, although precise, have a lower predictive ability than in FFNN-M3, with an R2 of 0.98621 and a higher RMSE of 0.0276. Overall, all the models presented the capability to estimate and enhance the strength characteristics of fiber-reinforced cement mortars, and the SWR models were identified as the most reliable tool. This insight is important for sustainable construction because accurate predictions can help to optimize fiber ratio for enhanced mix proportion, as proved by [41].

The results of observed and predicted values depicting the model's goodness of fit are compared in the scatter plot, as shown in Figure 6. The graphs showed good predictive accuracy for the models, especially when considering the coefficient of determination since the R^2 of all the models for all categories is recommendable, especially for the SWR models with values close to one for the SWR-M2 model. This suggests its advantage in identifying the independent variables that provide an optimal fit for the model. For both FFNN and SVM, a high R^2 value is observed also. Although the SVM models have good fits, the spread between the observed and predicted values is slightly higher, indicating a lower fit than the FFNN and SWR models. Concisely, the plots reveal that all models verify a strong fit with FFNN-M2, and the SWR-M2 has the highest accuracy. The results indicated that the employed models are ideal for simulating the complex relationships between the predictor variables' characteristics. Such minor variations between models may be due to parameter calibration or the intrinsic capability of the underlying algorithm to perform on a specific data set.

Figure 7 presents a radar plot that compares the R^2 values for three AI models (FFNN, SVM, and SWR) in predicting the fabric fiber strength of cement mortar made with PC. FFNN and SWR demonstrate the highest accuracy with $R^2 \approx 1$ in training, and SWR has high values in testing, indicating excellent predictive performance. SVM also performs slightly lower than SWR and FFNN but is still predicted well. Overall, SWR is the best model, followed by FFNN and SVM. Figure 8 presents the RMSE in training and testing sets of various AI models used in this study. It is seen that the RMSE values identify the SWR models with the best fit having the lowest RMSE. However, the FFNN models (as FFNN-M3) display a greater RMSE on the testing data than on the training data, implying possible over-learning. whereas the SVM models demonstrate moderate RMSE between testing and training with less accuracy. The proposed SWR generally achieves the highest predictive accuracy, while the FFNN and SVM also have comparatively high prediction accuracy. The wide-ranging conclusions showed the usefulness of machine learning models, particularly for sustainable waste management in the construction industry. This analysis presents valuable information for selecting models to forecast the impact of fabric fiber strength on cement mortar characteristics. It also gives an insight into considering the model's robustness apart from model accuracy when comparing different modeling approaches to ensure the suitability of the data structure and requirements in terms of the predictions.

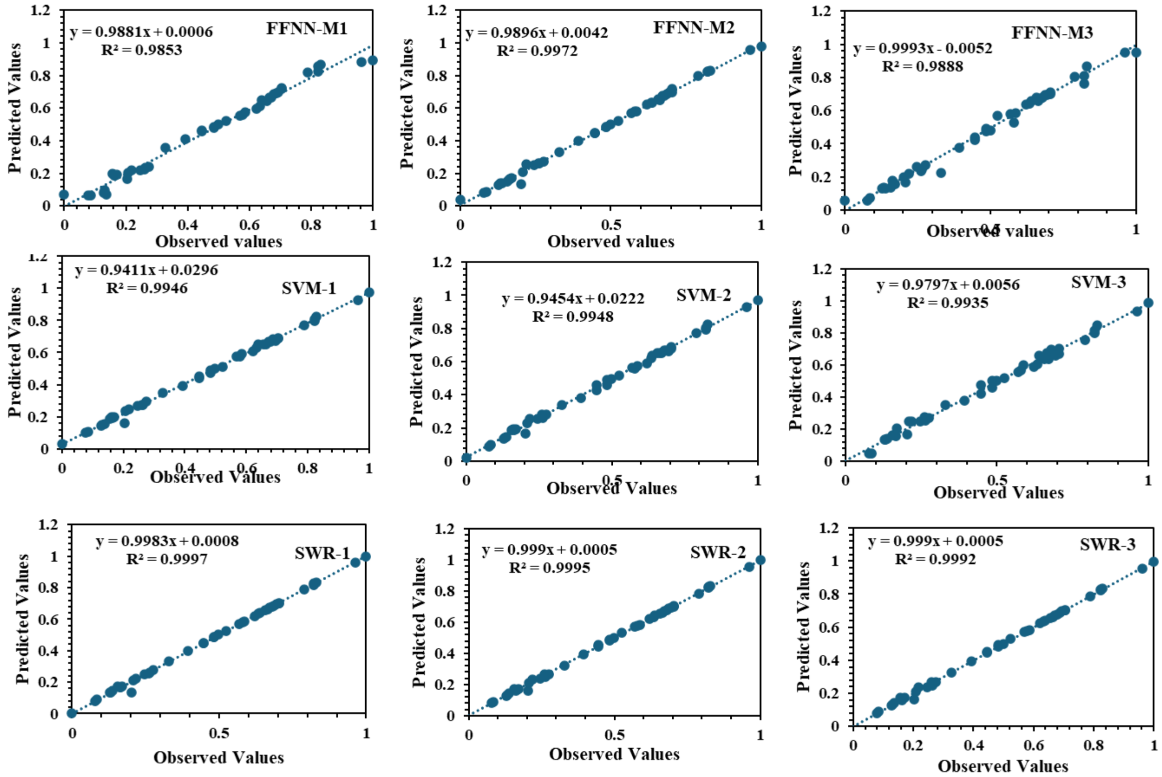

Figure 6: *Scatter plots for the FFNN, SVM, and SWR models*

Figure 7: *Radar plots of the generated models*

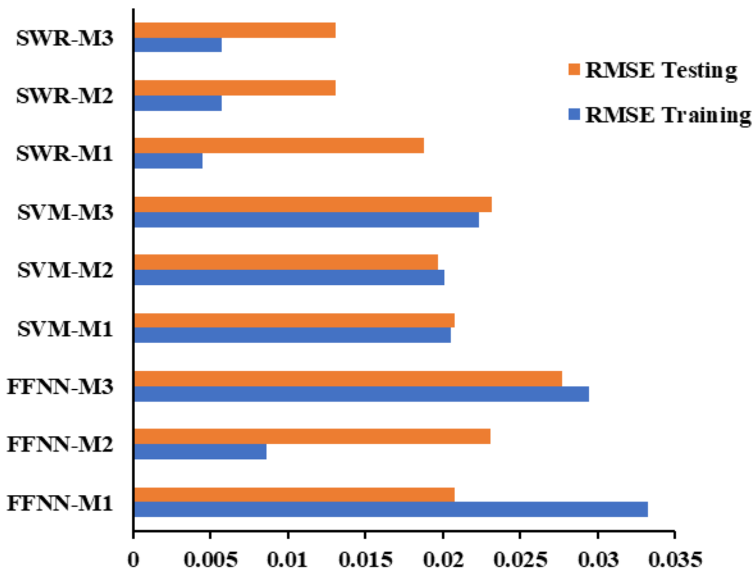

Figure 8: *Error plots for the generated models*

4. Conclusion

This paper establishes the efficiency of AI models, particularly FFNN, SVM, and SWR, in estimating the compressive strength of cement mortar with fabric fiber additives in different proportions (0.5%, 1%, 1.5%, and 2%). The experimental analysis revealed that increasing fabric fiber content enhances some mortar properties, such as crack resistance while decreasing the compressive strength with high fabric fiber contents (1.5% and 2%). Among all the AI models analyzed SWR models provided the best efficiency in predictive accuracy with FFNN and SVM when compared to other AI models, with the SWR-M2 model having the best evaluation performance with the highest R^2 of 99.97% in the training phase and 99.67% in the testing phase, with minimum RMSE of 0.00571. Contrary to other models, it is the most suitable for capturing the complex relationship of mortar composition. These results indicate that the AI models, especially the SWR model, can capture relationships of variable parameters in cement mortar composition. Also, the work shows the importance of the proper proportion of fiber to cement mortars for optimized durability and strength, as excess fiber reduces the compressive strength due to probable harmful interference with the cement matrix. In summary, this work laid the premise for integrating AI models to employ a sustainable construction approach, guiding the selection of fiber content for improved structural performance while offering insights for future applications in optimizing material compositions for specific construction needs. Moreover, Future research could evaluate long-term performance under different environmental conditions, and refining advanced AI models could offer valuable insights for optimizing cement-based materials in various construction scenarios.

Competing Interests: The authors declare no competing interests.

Data Availability Statement: The supported data associated with this researcher is available upon request from the corresponding author.

References

[1] L. Gil, E. Bernat-Masó, and F. J. Cañavate, "Changes in properties of cement and lime mortars when incorporating fibers from end-of-life tires," *Fibers*, vol. 4, no. 1, pp. 1–13, 2016, doi: 10.3390/fib4010007.

[2] G. Di Bella, V. Fiore, G. Galtieri, C. Borsellino, and A. Valenza, "Effects of natural fibres reinforcement in lime plasters (kenaf and sisal vs. Polypropylene)," *Constr. Build. Mater.*, vol. 58, pp. 159–165, 2014, doi: 10.1016/j.conbuildmat.2014.02.026.

[3] R. Illampas, I. Rigopoulos, and I. Ioannou, "Development and performance evaluation of a novel high-ductility fiber-reinforced lime-pozzolana matrix for textile reinforced mortar (TRM) masonry strengthening applications," *Mater. Struct. Constr.*, vol. 57, no. 4, pp. 1–28, 2024, doi: 10.1617/s11527-

024-02340-y.
[4] D. Ferrández, A. Zaragoza-Benzal, R. Pastor Lamberto, P. Santos, and J. Michalak, "Optimizing Masonry Mortar: Experimental Insights into Physico-Mechanical Properties Using Recycled Aggregates and Natural Fibers," *Appl. Sci.*, vol. 14, no. 14, 2024, doi: 10.3390/app14146226.
[5] M. A. Sanjrani, X. Gang, and S. N. A. Mirza, "A review on textile solid waste management: Disposal and recycling," *Waste Manag. Res.*, Jul. 2024, doi: 10.1177/0734242X241257093/ASSET/IMAGES/LARGE/10.1177_0734242X241257093-IMG2.JPEG.
[6] D. I. Alves, M. Barreiros, R. Fangueiro, and D. P. Ferreira, "Valorization of textile waste: non-woven structures and composites," *Front. Environ. Sci.*, vol. 12, no. February, pp. 1–23, 2024, doi: 10.3389/fenvs.2024.1365162.
[7] A. Singh, "Integration of Waste Management in Textile Industries of India," *Indian Sci. J. Res. Eng. Manag.*, vol. 08, no. 07, pp. 1–13, Jul. 2024, doi: 10.55041/IJSREM36458.
[8] S. Abrishami, A. Shirali, N. Sharples, G. E. Kartal, L. Macintyre, and O. Doustdar, "Textile Recycling and Recovery: An Eco-friendly Perspective on Textile and Garment Industries Challenges," *Text. Res. J.*, 2024, doi: 10.1177/00405175241247806.
[9] M. Ambrus and G. Mucsi, "Open-loop recycling of end-of-life textiles as geopolymer fibre reinforcement," *Waste Manag. Res.*, 2024, doi: 10.1177/0734242X241242708.
[10] A. Mamun, N. Torst, and L. Sabantina, "Advancing towards a Circular Economy in the Textile Industry," *Eng. Proc.*, vol. 56, no. 1, pp. 1–6, 2023, doi: 10.3390/ASEC2023-15244.
[11] T. Biswal, "Biopolymeric conjugation with synthetic fibers and applications," *Phys. Sci. Rev.*, vol. 9, no. 9, pp. 2827–2849, Sep. 2023, doi: 10.1515/PSR-2022-0183/MACHINEREADABLECITATION/RIS.
[12] H. ALSAYADI, N. KHALDI, H. HEBHOUB, C. RIHIA, M. I. BENHALILOU, and K. MESSAOUDI, "Effect of Recycled Fibers on the Mechanical Properties and Durability of Sand Concrete," *Mater. Sci.*, vol. XX, no. X, 2024, doi: 10.5755/j02.ms.36236.
[13] R. Ayed, *Use of Textile Fiber Waste to Improve the Thermal and Mechanical Performance of Cement-Based Mortar*, vol. 2. Springer Nature Switzerland. doi: 10.1007/978-3-031-57800-7.
[14] Y. Weng, B. Lu, M. Li, Z. Liu, M. Jen, and S. Qian, "Empirical models to predict rheological properties of fiber reinforced cementitious composites for 3D printing," *Constr. Build. Mater.*, vol. 189, pp. 676–685, 2018, doi: 10.1016/j.conbuildmat.2018.09.039.
[15] A. Shams, M. Horstmann, and J. Hegger, "Experimental investigations on Textile-Reinforced Concrete (TRC) sandwich sections," *Compos. Struct.*, vol. 118, pp. 643–653, 2014, doi: 10.1016/j.compstruct.2014.07.056.
[16] L. A. Abdulateef and A. M. Ahmed, "Exploring the Mechanical Behavior of Concrete enhanced with Fibers derived from recycled Plastic Bottles," vol. 14, no. 2, pp. 13481–13486, 2024.
[17] L. A. Pereira-de-oliveira, J. P. Castro-gomes, and M. C. S. Nepomuceno, "Effect of acrylic fibres geometry on physical , mechanical and durability properties of cement mortars," *Constr. Build. Mater.*, vol. 27, no. 1, pp. 189–196, 2012, doi: 10.1016/j.conbuildmat.2011.07.061.
[18] S. Hanumanthappa and P. Ramya, "The influence of blended polypropylene and polyethylene fibres on mechanical and durability properties of concrete," *Mater. Today Proc.*, vol. 88, pp. 19–28, Jan. 2023, doi: 10.1016/J.MATPR.2023.04.459.
[19] M. Bentchikou, A. Guidoum, K. Scrivener, K. Silhadi, and S. Hanini, "Effect of recycled cellulose fibres on the properties of lightweight cement composite matrix," *Constr. Build. Mater.*, vol. 34, pp. 451–456, 2012, doi: 10.1016/j.conbuildmat.2012.02.097.
[20] S. Spadea, I. Farina, A. Carrafiello, and F. Fraternali, "1409.7258.Pdf".
[21] P. Dalmay, C. Patapy, C. Peyratout, A. Smith, and T. Chotard, "Journal of Composite Materials," no. April, 2011, doi: 10.1177/0021998311401088.
[22] E. Olyaie, H. Abyaneh, A. M.-G. Frontiers, and undefined 2017, "A comparative analysis among computational intelligence techniques for dissolved oxygen prediction in Delaware River," *ElsevierE Olyaie, HZ Abyaneh, AD MehrGeoscience Front. 2017•Elsevier*, Accessed: Oct. 17, 2024. [Online]. Available: https://www.sciencedirect.com/science/article/pii/S1674987116300469
[23] C. Grosan and A. Abraham, "Artificial Neural Networks," vol. 17, pp. 281–323, Jan. 2011, doi: 10.1007/978-3-642-21004-4_12.
[24] J. Zou, Y. Han, and S.-S. So, "Overview of Artificial Neural Networks," *Methods Mol. Biol.*, vol. 458, pp. 14–22, Jan. 2009, doi: 10.1007/978-1-60327-101-1_2.
[25] R. Mahadeva *et al.*, "Improvised grey wolf optimizer assisted artificial neural network (IGWO-ANN) predictive models to accurately predict the permeate flux of desalination plants," *Heliyon*, vol. 10, no. 13, p. e34132, 2024, doi: 10.1016/j.heliyon.2024.e34132.
[26] Y. Huang, Y. Lei, X. Luo, and C. Fu, "Prediction of compressive strength of rice husk ash concrete: A comparison of different metaheuristic algorithms for optimizing support vector regression," *Case Stud. Constr. Mater.*, vol. 18, p. e02201, 2023, doi: https://doi.org/10.1016/j.cscm.2023.e02201.
[27] X. Zhang, C. Dai, W. Li, and Y. Chen, "Prediction of compressive strength of recycled aggregate concrete using machine learning and Bayesian optimization methods," *Front. Earth Sci.*, vol. 11, no. February, pp. 1–16, 2023, doi: 10.3389/feart.2023.1112105.
[28] C. Fan, Y. Zheng, S. Wang, and J. Ma, "Prediction of bond strength of reinforced concrete structures based on feature selection and GWO-SVR model," *Constr. Build. Mater.*, vol. 400, p. 132602, 2023, doi: https://doi.org/10.1016/j.conbuildmat.2023.132602.
[29] S. Mariatul, H. Mohd, A. Fawwaz, M. Amidon, A. Hazirah, and I. Hasnu, "Stepwise regression of agarwood oil significant chemical compounds into four quality differentiation," vol. 29, no. 2, pp. 735–

741, 2023, doi: 10.11591/ijeecs.v29.i2.pp735-741.

[30] G. Papazafeiropoulos, "Stepwise Regression for Increasing the Predictive Accuracy of Artificial Neural Networks : Applications in Benchmark and Advanced Problems," pp. 153–179, 2024.

[31] J. Nathan Kutz, "Machine Learning Methods for Constructing Dynamic Models From Data," pp. 149–178, 2023, doi: 10.1007/978-3-031-36644-4_4.

[32] M. A. Waris, M. Nayab, U. Shafiq, U. Imran, and A. Waris, "Examining the Impact of Different K Values on the Performance of Multiple Algorithms in K-Fold Cross-Validation," *ieeexplore.ieee.orgU Imran, A Waris, M Nayab, U Shafiq2023 3rd Int. Conf. Digit. Futur. and, 2023•ieeexplore.ieee.org*, doi: 10.1109/ICoDT259378.2023.10325695.

[33] B. Erdebilli and B. Devrim-İçtenbaş, "Ensemble Voting Regression Based on Machine Learning for Predicting Medical Waste: A Case from Turkey," *Mathematics*, vol. 10, no. 14, pp. 7–9, 2022, doi: 10.3390/math10142466.

[34] S. Jahandideh *et al.*, "The use of artificial neural networks and multiple linear regression to predict rate of medical waste generation," *Waste Manag.*, vol. 29, no. 11, pp. 2874–2879, 2009, doi: 10.1016/j.wasman.2009.06.027.

[35] X. C. Nguyen *et al.*, "Resources , Conservation & Recycling Development of machine learning - based models to forecast solid waste generation in residential areas : A case study from Vietnam," *Resour. Conserv. Recycl.*, vol. 167, no. January, p. 105381, 2021, doi: 10.1016/j.resconrec.2020.105381.

[36] A. Karpušenkaite, T. Ruzgas, and G. Denafas, "Forecasting medical waste generation using short and extra short datasets: Case study of Lithuania," *Waste Manag. Res.*, vol. 34, no. 4, pp. 378–387, 2016, doi: 10.1177/0734242X16628977.

[37] S. I. Malami *et al.*, "Implementation of soft-computing models for prediction of flexural strength of pervious concrete hybridized with rice husk ash and calcium carbide waste," *Model. Earth Syst. Environ.*, vol. 8, no. 2, pp. 1933–1947, Jun. 2022, doi: 10.1007/S40808-021-01195-4/METRICS.

[38] S. I. Abba, A. G. Usman, and S. IŞIK, "Simulation for response surface in the HPLC optimization method development using artificial intelligence models: A data-driven approach," *Chemom. Intell. Lab. Syst.*, vol. 201, no. August 2019, 2020, doi: 10.1016/j.chemolab.2020.104007.

[39] W. Zhang and X. Li, "Linear correlation analysis in finding interactions : Half of predicted interactions are undeterministic and one-third of candidate direct interactions are missed," vol. 2, no. 3, pp. 39–45, 2015.

[40] N. M. Nielsen, W. A. C. Smink, and J. P. Fox, "Small and negative correlations among clustered observations: limitations of the linear mixed effects model," *Behaviormetrika*, vol. 48, no. 1, pp. 51–77, 2021, doi: 10.1007/s41237-020-00130-8.

[41] X. Qin and S. Kaewunruen, "Eco-Friendly Design and Sustainability Assessments of Fibre-Reinforced High-Strength Concrete Structures Automated by Data-Driven Machine Learning Models," *Sustain.*, vol. 15, no. 8, 2023, doi: 10.3390/su15086640.