MACHINE LEARNING BASED PREDICTION FOR COMPRESSIVE STRENGTH OF HYBRID FIBER-REINFORCED CONCRETE

Ladunnee Biswas*[1], Md. Habibur Rahman Sobuz[2] and Sumaiya Mifra Akhter[3]

[1] *Graduate student, Khulna University of Engineering & Technology, Bangladesh,*
e-mail: laduneebiswas1998@gmail.com
[2] *Associate Professor, Khulna University of Engineering & Technology, Bangladesh,*
e-mail: habib@becm.kuet.ac.bd
[3] *Graduate student, Khulna University of Engineering & Technology Bangladesh,*
e-mail: sumayamifraakter@gmail.com

***Corresponding Author**

ABSTRACT

One of the most promising building methods and repair materials in recent years for the construction industry is hybrid fiber reinforced concrete (HFRC). Plain concrete typically has very little tensile strength and just a small amount of resistance to breaking before the ultimate load. In concrete buildings, fiber hybridization with various fiber types aids in preventing these cracks. The prediction of strength, in Hybrid Fiber Reinforced Concrete (HFRC) is still in its stages, which poses a challenge compared to traditional concrete. This challenge arises because HFRC formulations are complex and there is data for accurate predictions. Unlike concrete HFRC has a composition, with various fibers mixed together requiring a more detailed understanding and customized modeling techniques to predict its Compressive strength accurately. . To overcome this limitation, research was conducted to develop an optimum machine learning algorithm for predicting the compressive strengths of HFRC This research aims to explore the most effective machine learning algorithms for predicting HFRC compressive strength accurately. To achieve this, compressive strength data from HFRC were collected through extensive literature reviews, and a database was created. On the basis of the dataset, eight machine learning algorithms were developed. To avoid overfitting, K-fold validation was done, and the algorithms were controlled. Random-forest regression, Decision tree regression, Linear regression and Support vector regression (SVR) models all looked to perform well in predicting the actual measurements. KNN, ANN, RNN and CNN models, on the other hand, displayed relatively wide deviation, with gaps from the center line, resulting in considerable deviations from the real observations. In general, the regression-based ensemble approaches performed well, and the neural network-based algorithms generally performed admirably. The most important variables in predicting the compressive strength of HFRC were age of concrete and steel fiber.

Keywords: *Hybrid Fiber Reinforced Concrete, Machine learning, Strength prediction, Compressive strength*

1. INTRODUCTION

Concrete is a material that is utilized extensively in the construction industry and requires desirable engineering properties that will significantly boost the economy. The primary function of concrete is to support loads over an extended period of time, even if many concretes can be created by creating intentional designs [1]. Carrying capacity, or the desired attribute, can now be easily obtained in all concretes made and utilized in buildings. The most significant characteristic of concrete is its compressive strength, which increases with time and flawlessly fulfills its role against compressive loads of concrete. Concrete's longevity is greatly impacted by cracks that can occur for a variety of reasons, making it a material that is weak against tensile loads. Concrete behaves brittlely due to its low tensile strain capacity, making cracks in concrete buildings nearly inevitable [2]. Innovative studies conducted in the last few decades have demonstrated that adding a certain amount of fiber can enhance the mechanical properties of HFRC [3]. Steel fiber (SF) and polypropylene fiber (PPF) are two of the most commonly utilized types of fibers because of their outstanding resistance to shrinkage cracking, low cost, and relatively high toughness [5].

Numerous studies indicate that while polypropylene fiber greatly increases the ductility of the HFRC and prevents explosive spalling, it has no effect on the compressive strength. The mechanical characteristics of HRFC can be enhanced by the addition of polypropylene fiber at a percentage ranging from 0.3% to 0.9% [4]. The mechanical characteristics of HFRC experienced a partial decline at dosages more than 0.9%. The ductility of HFRC is significantly enhanced by the inclusion of steel fibers, which can also change the failure morphology and enhance the mechanical properties of the material. Prediction models of the mechanical properties of normal concrete have been proposed in a number of studies; however, compared to normal concrete, HFRC has more variables that can be forecasted, including fiber type, water cement ratio, aging time and condition, and mix proportion of fiber [6]. Consequently, the creation of appropriate prediction models for HFRC is still in its infancy. This makes it difficult to predict the compressive strengths of SFRC with conventional linear or nonlinear regression methods. Machine-learning algorithms can potentially solve the problem of HFRC compressive strength prediction. There have been very few machine learning-based prediction studies of HFRC since it is difficult to collect data for models with various variables (such as fiber type, aging time, etc.). Furthermore, no published research has yet determined the proper techniques for predicting compressive strength. Consequently, this study builds a machine-learning model that predicts the compressive strength of HFRC and compares several methods to determine which works best.

8 different algorithms were used during this study to build a machine-learning model. Boosting-based algorithms, random forests, decision trees, K-nearest neighbor, and linear algorithms were taken into consideration. Overfitting is the most important consideration when utilizing machine-learning algorithms. Overfitting causes the model to become unstable when more external data are applied and the data are overlearned. In order to prevent overfitting, K-fold validation was used in this study, and the model was adjusted if it was discovered to have occurred. The best methods for estimating the strength of the HFRC were identified by comparing and analyzing the machine learning models generated by each approach. Furthermore, variables that were found to be significant in forecasting through model prediction.

2. METHODOLOGY

Data preprocessing

To determine which data to use, the dataset must be preprocessed before creating the machine-learning models. 8 references [7-14] provided the data that was gathered for this investigation. 137 sets of compressive strengths in all were employed. Because the purpose of this research is to establish first HFRC machine-learning models and predict mechanical properties, the dataset was created exclusively using data from concrete that was reinforced with steel and polypropylene fibers. The dataset had a large number of variables, but only those that were found to have a fundamental effect were selected and preprocessed.

As a result, the dataset had seven features in total—seven input data and two output data. Cement, water, coarse and fine aggregates, steel and polypropylene fibers, and the concrete's age were among the input data. Due to the fact that compressive strengths are fundamental mechanical qualities that are influenced by each feature, numerous prior research have examined compressive strengths concurrently, which is why the seven features were taken into account for the HFRC's compressive strength predictions. The following are the ways that each characteristic affects compressive strength:

Concrete's durability properties are influenced by multiple aspects, including water-to-cement ratio, cement type, and quality. The choice and grading of aggregates, such as polypropylene and steel, affects strength and performance. Age also affects these properties, requiring careful combination and proportioning to achieve exceptional strength, durability, and overall performance.

Evaluation method

Mean Absolute Error (MAE), Mean Square Error (MAPE), Root Mean Square error (RMSE), and Co-efficient of determination (R^2) were taken into consideration while assessing the accuracy of machine-learning algorithms.

Mean Absolute Error (MAE)

A statistic called Mean Absolute Error (MAE) is used, especially in regression analysis, to assess how accurate a predictive model is. It calculates the mean absolute difference between the values that were expected and the values that were observed [4].

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|y - y'|$$

Here, y is the actual value, y' is the predicted value and n is the number of data samples.

Mean Square Error (MSE)

One popular statistic used in regression analysis to assess a predictive model's accuracy is Mean Squared Error (MSE). It calculates the mean of the squared discrepancies between the actual and anticipated values. Larger errors are penalized by MSE more severely because of the squaring operation.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y' - y)^2$$

Root Mean Square Error (RMSE)

Regression analysis uses the Root Mean Squared Error (RMSE) statistic to assess a predictive model's accuracy. It measures the normal number of mistakes and penalizes greater errors more severely. Lower RMSE values indicate improved model accuracy, making it helpful [4].

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y' - y)^2}$$

Co-efficient of determination (R^2)

Regression analysis uses the coefficient of determination, or R^2, as a statistical metric to determine how much of the variance in the dependent variable can be attributed to the independent variables. On a scale of 0 to 1, 1 denotes an ideal fit and 0 denotes no explanatory power. By comparing the variance of the actual values to the variance of the projected values, the R^2 value is determined. A model that fits the data better is indicated by a higher R^2 value [19].

$$R^2 = 1 - \frac{\sum (y - y')^2}{\Sigma(y - \bar{y})^2}$$

$\bar{y}$ is the average value

Where y is the actual value, y' is the predicted value and

Machine-learning algorithms

In this study, a variety of machine-learning algorithms were used for predicting the compressive strength of HFRC and to identify appropriate algorithms for use as the predictive models. Convolutional Neural Network (CNN), Recurrent Neural Network (RNN), Artificial Neural Network (ANN), K-Nearest Neighbors (KNN), Linerar regressor, Random forest regressor, Decision tree regression, Support vector regression were used as machine-learning models. To ensure the model's dependability, the significance of the feature of the models that performed well was evaluated and compared with the findings of previous studies.

Recurrent Neural Network (RNN)

A CSV file containing columns for cement, water, aggregates, fibers, age, and compressive strength is loaded by the code. The train test split function divides the dataset into training and testing sets. Scikit-Learn's Standard Scaler is used to standardize features. In order to meet the specifications of an LSTM model, the input data is reshaped. The features are treated as a sequence and the array is converted from two dimensions to three dimensions. An LSTM layer with 50 units and a ReLU activation function is followed by an output layer with one neuron for regression in a sequential model built using Keras. The mean squared error is used as the loss function and the Adam optimizer is used to compile the model. Using a batch size of 32, the RNN model is trained for 50 epochs on the reshaped training data. During training, monitoring is done using validation data. On the test set, the trained model predicts compressive strength. Mean squared error, root mean square error, and mean absolute error are computed and presented as evaluation metrics.

Lose function formula , $v_t = \beta . v_t + (1 - \beta)[grad(\theta_{t-1})]^2$

K-Nearest Neighbors (KNN)

A CSV file comprising columns for cement, water, aggregates, fibers, age, and compressive strength is used to load the dataset. A CSV file comprising columns for cement, water, aggregates, fibers, age, and compressive strength is used to load the dataset. To guarantee uniform scaling across variables, features are standardized using scikit-learn's StandardScaler. Using the KNeighbors, the KNN model is constructed with the provided number of neighbors (k=5).from scikit-learn regression. Compressive strength on the test set is predicted by the model. The model's performance is shown by the computation and printing of mean squared error, root mean square error, and mean absolute error. For fetching nearrest neighbour from KNN we used euclidian distance.

$$d = \sqrt{(x - x_i)^v + (y - y_i)^2 + \cdots .. + (z - z_i)^2}$$

Convolutional Neural Network (CNN)

The code loads a CSV file that has columns for cement, water, aggregates, fibers, age, and compressive strength. The dataset is split into training and testing sets using the train_test_split function. StandardScaler from Scikit-Learn is used to standardize features. The input data is altered in order to make it compatible with a 1D convolutional layer. Samples, features, 1 is the sequence that each feature becomes to construct a 3D array with dimensions. A sequential model with one neuron for regression in the output layer, max-pooling, flattening, dense layer with 64 neurons with ReLU activation, and 1D convolutional layer with 64 filters is constructed using Keras. The model is assembled using the Adam optimizer, and the loss function is the mean squared error. The CNN model is trained on the reshaped training set for 50 epochs with a batch size of 32. Validation data is used for monitoring during training. The training model predicts compressive strength on the test set. As evaluation metrics, mean squared error, root mean square error, and mean absolute error are calculated and displayed.

Artificial Neural Network (ANN)

The code loads an actual attribute dataset from a CSV file. It specifically collects parameters and the target variable, including age, compressive strength, water, fibers, aggregates, and cement. The dataset is split into training and testing sets using the scikit-learn train_test_split function, with 80% of the data being used for training and 20% for testing. The StandardScaler is used to standardize features in order to ensure consistent scaling across variables. A sequential model is constructed using Keras, with 128 neurons in the input layer with ReLU activation, 64 neurons in the hidden layer with ReLU activation, and one neuron for regression in the output layer. The model is assembled using the Adam optimizer, and the loss function is the mean squared error. The ANN is trained on the scaled training data for 50 epochs with a batch size of 32. Validation data is used for monitoring during training. On the test set, the trained model predicts the compressive strength. Evaluation metrics like mean squared error, root mean square error, and mean absolute error are also computed and printed by it.
ReLU formula is = f(x) = max (0,x)

Linear Regression

Linear regression is a widely used supervised learning-based machine learning prediction algorithm used to predict the connection between a dependent variable and independent variables. It aims to minimize discrepancies between actual and anticipated values, using methods like ordinary least squares to estimate linear equation parameters [4]. Therefore, this regression technique identifies a linear relationship between input (Xn) and output (y) as follows:

$$\hat{y} = \theta_0 + \theta_1 X_1 + \cdots + \theta_n X_n$$

Decision Tree Regression

Decision tree regression is a machine learning approach used for predictive modeling in regression tasks. It uses a tree structure with leaf nodes representing expected results and inside nodes representing decisions. The algorithm aims to reduce variance, handle non-linear correlations, and handle both numerical and categorical data [20]. The formula as follows:

$$J(\theta) - m_L MSE_L + m_R MSE_R / m$$

$$MSE_{node} = \sum_{i \epsilon node} (y - \hat{y})^2 / 2\, m_{node}$$

Random forest regressor

Several decision tree regressors are used in Random Forest Regression, an ensemble learning technique, to improve prediction accuracy. By building a "forest" of trees trained on arbitrary subsets of characteristics and data, the model enhances generalization and reduces overfitting. The Random Forest Regression technique is widely acknowledged for its resilience, adaptability to various data formats, and capacity to identify complex patterns within the data [21].

Support Vector Regression (SVR)

A machine learning approach called Support Vector Regression (SVR) is intended for regression tasks. It finds the hyperplane that best depicts the relationship between the input variables and the continuous output by applying the concepts of support vector machines. SVR seeks to reduce error while permitting a tolerance margin. It works very well at identifying intricate patterns and nonlinear correlations in the data [22].

3. RESULTS AND DISCUSSION

Several machine-learning algorithms were used to predict the compressive strengths of HFRC. The practicality of machine-learning algorithms was demonstrated by comparing the projected and actual values, and the feature significance of the four methods that performed quite well was thoroughly examined to ensure the models' reliability.

Table 01 shows the machine learning prediction for Neural Networks Models of compressive strength of HFRC. By estimating the compressive strength using several machine learning models, it was discovered that the KNN (K-Nearest Neighbors) approach had the best machine learning performance model, with MSE, RMSE, and MAE of 60.17, 7.75, and 6.27, respectively. K-Nearest Neighbors (KNN) is a particularly interesting model because of its quick computation time and reliable prediction performance. On the other hand, models with the intrinsic property of continuously changing values in every training epoch, such as Recurrent Neural Networks (RNN), Convolutional Neural Networks (CNN), and Artificial Neural Networks (ANN), are not taken into consideration. KNN is a sensible option because of its steady performance and computational efficiency, which spares it from the volatility brought on by deep learning models' repetitive modifications.

These metrics such as MAE, MSE, RMSE & R^2 are usually compared between models to determine which one works best for predicting the compressive strength of HFRC. Better predictive accuracy is indicated by lower MAE, MSE, and RMSE values, and a stronger correlation between the expected and actual compressive strength values is indicated by a higher R^2 value. All of these measurements work together to provide crucial tools for selecting and evaluating models when estimating the compressive strength of hybrid fiber-reinforced concrete.

Table 01: Results for machine learning algorithms for compressive strength (Neural Networks)

	Error	CNN	RNN	ANN	KNN	Remarks
1st Case	MSE	198.21	198.21	186.24	60.17	
	RMSE	14.07	14.07	13.67	7.75	KNN
	MAE	12.15	12.15	11.38	6.27	
2nd Case	MSE	197.51	197.51	176.14	60.17	
	RMSE	14.05	14.05	13.27	7.75	KNN
	MAE	12.03	12.03	10.97	6.27	
3rd Case	MSE	207.75	207.75	185.49	60.17	
	RMSE	14.41	14.41	13.62	7.75	KNN
	MAE	12.55	12.55	11.29	6.27	
4th Case	MSE	204.91	204.91	204.49	60.17	
	RMSE	14.31	14.31	14.4	7.75	KNN
	MAE	12.41	12.41	11.33	6.27	
5th Case	MSE	208.06	208.06	193.81	60.17	
	RMSE	14.42	14.42	13.92	7.75	KNN
	MAE	12.55	12.55	11.57	6.27	
6th Case	MSE	199.61	199.61	193.76	60.17	
	RMSE	14.13	14.13	13.91	7.75	KNN
	MAE	12.17	12.17	11.67	6.27	

Table 02: Results for machine learning algorithms for compressive strength (Regression)

Regression Algorithms	MSE	RMSE	MAE	R^2
Linear regression	38.33	6.19	4.81	0.72
Random forest regression	24.36	5.9	4.03	0.82
Decision tree regression	34.81	4.9	5.2	0.7
Support vector regression (SVR)	61.81	7.86	6.30	0.71

Regression models are analyzed in Table 02; of the regression techniques examined. This demonstrates even more how well regression models work to estimate the compressive strength of HFRC. In Figure 04, one can see that Regression models, especially Random Forest Regression, appear to perform better than neural network models in terms of predicting accuracy for HFRC compressive strength, according to the comparison between the two types of models. Regression models are the better option for this particular prediction task because of their increased stability and dependability.

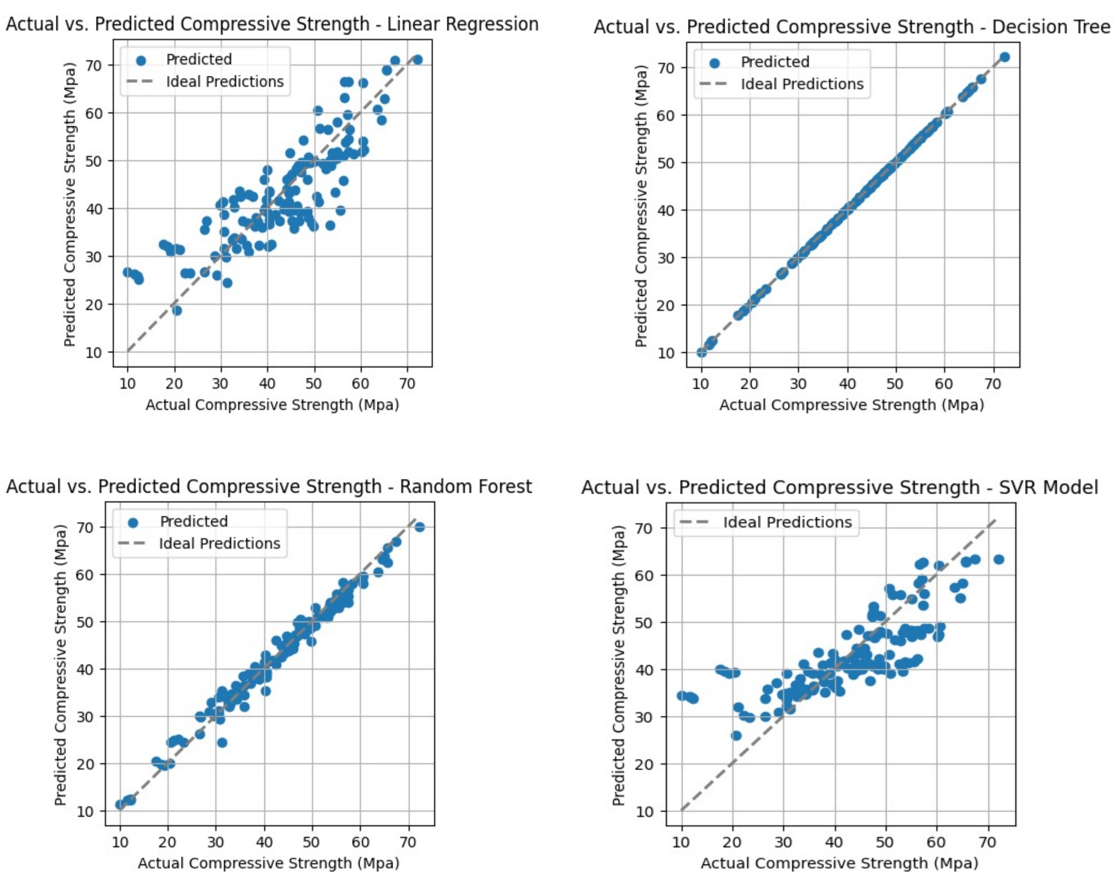

Figure 01: Comparison of actual and predicted compressive strength with various algorithms

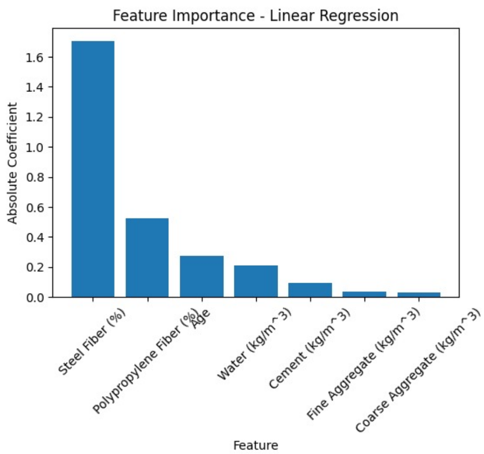

Figure 02: Important variables for Linear Regression

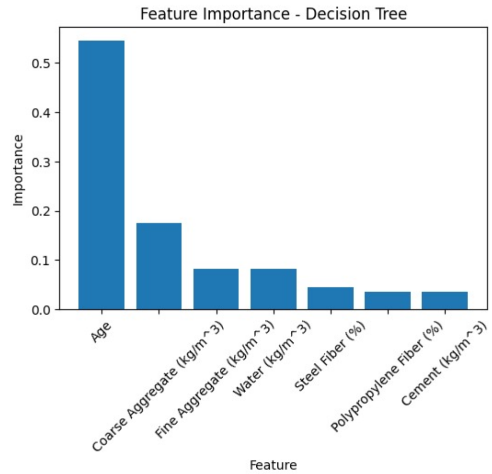

Figure 03: Important variables for Decision Tree regression

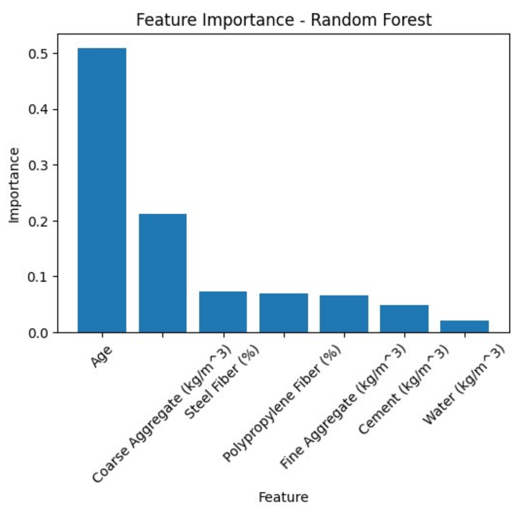

Figure 04: Important variables for Random Forest Regression

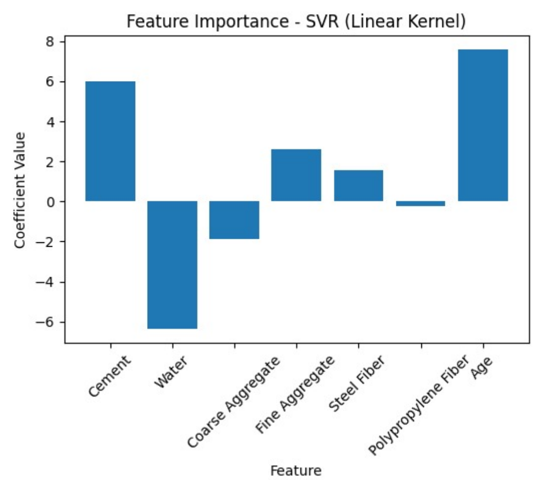

Figure 05: Important variables for Support Vector Regression (SVR)

In Figure 2, Figure 03, Figure 04 & Figure 05, the four best predictive algorithms are compared for feature importance. The analysis showed that, relative to other variables, steel fiber, age of concrete, aggregate size, water were factors dominating the compressive strength of HFRC. On the contrast, polypropylene fiber, cement mix ratio has different role in different models. In SVR, water, coarse aggregate and polypropylene fiber shows a negative histogram because Support Vector Regression (SVR) with a linear kernel, indicates an inverse relationship between the feature and the target variable. In other words, as the value of the feature decreases, the predicted target value is expected to increase.

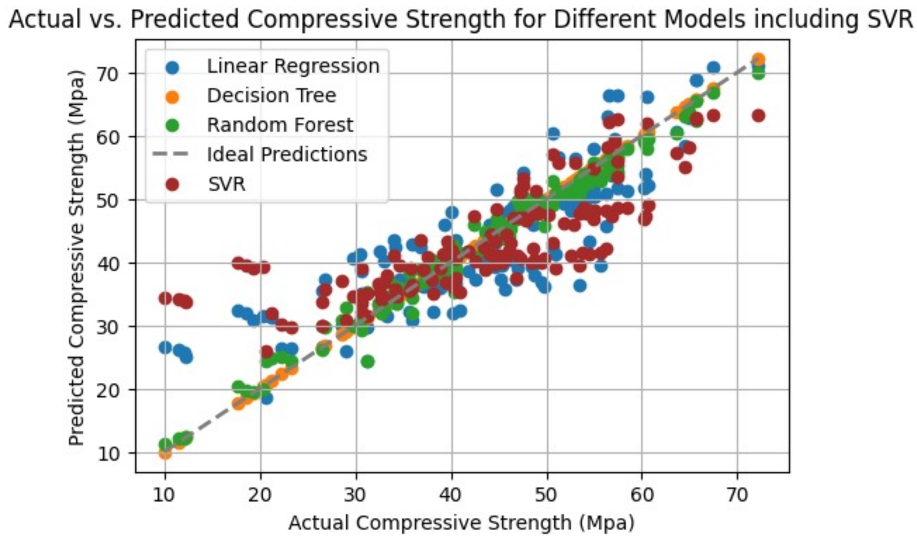

Figure 06: Actual vs predicted compressive strength for all models

Figure 6 shows a comparison of the hybrid fiber reinforced concrete's (HFRC) actual and projected compressive strengths. Interestingly, even with a low Root Mean Squared Error (RMSE), the Decision Tree Regression exhibits minimal variance and closely approximates the real values. Even though Support Vector Regression (SVR) performs well in most cases, it occasionally produces outlier values, which could lead to higher error rates. As a result, in this particular study environment, Random Forest Regression turns out to be a better option for precisely estimating the compressive strength of HFRC. A better estimate would have an RMSE value between 4 and 6. A value between 0 and 2 suggests that the model was overfit and that the statistical method was not appropriate. So, the selected machine learning model should be Random Forest Regression and KNN considering their reliability.

4. CONCLUSIONS

In conclusion, the application of machine learning algorithms has resulted in positive outcomes in predicting the compressive strength of hybrid fiber-reinforced concrete (HFRC), with the most effective algorithms being Support Vector Regression (SVR), Random Forest Regression, Decision Tree Regression, and Linear Regression. Conversely, it was found that the prediction accuracy of K-Nearest Neighbors (KNN), Artificial Neural Networks (ANN), Recurrent Neural Networks (RNN), and Convolutional Neural Networks (CNN) was much lower. Among them, K-Nearest Neighbors (KNN) is a fast and efficient alternative to ANN, RNN, and CNN, offering real-time predictions without the need for explicit training stages, making it a popular choice for applications requiring immediate applicability.

The Random Forest Regression performed better than the other models when analyzed in terms of accuracy, depending to the regression study. Outliers affected the accuracy of the Support Vector Regression (SVR) model, even though it had the lowest Root Mean Squared Error (RMSE), indicating low overall prediction error. The Random Forest Regression is the recommended model for this particular analysis since it showed better accuracy in predicting the target variable, albeit with a possibly greater RMSE. Random Forest performed better overall in capturing the complicated relationships within the data, in part because of its resilience to outliers.

So, the best predictive models were K-Nearest Neighbors (KNN) and Random Forest Regression.

After a detailed analysis of the importance of numerous mix variables, the two most important variables in predicting the compressive strength of HFRC were the age of the concrete and the presence of steel fiber. This emphasizes how crucial it is to take these essential variables into account when developing and evaluating machine learning models that predict concrete strength.

The results highlight how crucial it is to comprehend the particular qualities and specifications of the concrete mix when using a machine learning method for predictive modeling. Moreover, the discovery that the age of the steel fiber and concrete are crucial factors emphasizes the necessity of a sophisticated approach to material composition and curing time in the HFRC design and assessment.

REFERENCES

1. Bankir, M. B., & Sevim, U. K. (2020). Performance optimization of hybrid fiber concrete according to mechanical properties. *Construction and Building Materials*, *261*, 119952.
2. Song, W., & Yin, J. (2016). Hybrid effect evaluation of steel fiber and carbon fiber on the performance of the fiber reinforced concrete. *Materials*, *9*(8), 704.
3. He, W., Kong, X., Fu, Y., Zhou, C., & Zheng, Z. (2020). Experimental investigation on the mechanical properties and microstructure of hybrid fiber reinforced recycled aggregate concrete. *Construction and Building Materials*, *261*, 120488.
4. Kang, M. C., Yoo, D. Y., & Gupta, R. (2021). Machine learning-based prediction for compressive and flexural strengths of steel fiber-reinforced concrete. *Construction and Building Materials*, *266*, 121117.
5. Sobuz, M. H. R., Khan, M. H., Kabbo, M. K. I., Alhamami, A. H., Aditto, F. S., Sajib, M. S., ... & Alam, A. (2024). Assessment of mechanical properties with machine learning modeling and durability, and microstructural characteristics of a biochar-cement mortar composite. *Construction and Building Materials*, *411*, 134281.
6. Banyhussan, Q. S., Yıldırım, G., Bayraktar, E., Demirhan, S., & Şahmaran, M. (2016). Deflection-hardening hybrid fiber reinforced concrete: The effect of aggregate content. *Construction and building materials*, *125*, 41-52.
7. Das, S., Sobuz, M. H. R., Tam, V. W., Akid, A. S. M., Sutan, N. M., & Rahman, F. M. (2020). Effects of incorporating hybrid fibres on rheological and mechanical properties of fibre reinforced concrete. *Construction and Building Materials*, *262*, 120561.
8. Song, W., & Yin, J. (2016). Hybrid effect evaluation of steel fiber and carbon fiber on the performance of the fiber reinforced concrete. *Materials*, *9*(8), 704.
9. Teja Prathipati, S. R. R., Rao, C. B. K., & Dakshina Murthy, N. R. (2020). Mechanical behavior of hybrid fiber reinforced high strength concrete with graded fibers. *International Journal of Engineering*, *33*(8), 1465-1471.
10. Almahameed, B. A. A., & Sobuz, H. R. (2023). The Role of Hybrid Machine Learning for Predicting Strength Behavior of Sustainable Concrete.
11. Quinino, U. C. D. M., Christ, R., Tutikian, B. F., & Silva, L. C. P. D. (2022). Statistical Modeling of Compressive Strength of Hybrid Fiber-Reinforced Concrete-HFRC. *Fibers*, *10*(8), 64.
12. Bankir, M. B., & Sevim, U. K. (2020). Performance optimization of hybrid fiber concrete according to mechanical properties. *Construction and Building Materials*, *261*, 119952.
13. Banyhussan, Q. S., Yıldırım, G., Bayraktar, E., Demirhan, S., & Şahmaran, M. (2016). Deflection-hardening hybrid fiber reinforced concrete: The effect of aggregate content. *Construction and building materials*, *125*, 41-52.

14. Ly, H. B., Le, T. T., Vu, H. L. T., Tran, V. Q., Le, L. M., & Pham, B. T. (2020). Computational hybrid machine learning based prediction of shear capacity for steel fiber reinforced concrete beams. *Sustainability*, *12*(7), 2709.
15. Kina, C., Turk, K., Atalay, E., Donmez, I., & Tanyildizi, H. (2021). Comparison of extreme learning machine and deep learning model in the estimation of the fresh properties of hybrid fiber-reinforced SCC. *Neural Computing and Applications*, *33*, 11641-11659.
16. Jiao, P., Roy, M., Barri, K., Zhu, R., Ray, I., & Alavi, A. H. (2019). High-performance fiber reinforced concrete as a repairing material to normal concrete structures: Experiments, numerical simulations and a machine learning-based prediction model. *Construction and Building Materials*, *223*, 1167-1181.
17. Yang, L., Qi, C., Lin, X., Li, J., & Dong, X. (2019). Prediction of dynamic increase factor for steel fibre reinforced concrete using a hybrid artificial intelligence model. *Engineering Structures*, *189*, 309-318.
18. Milad, A., Hussein, S. H., Khekan, A. R., Rashid, M., Al-Msari, H., & Tran, T. H. (2022). Development of ensemble machine learning approaches for designing fiber-reinforced polymer composite strain prediction model. *Engineering with Computers*, *38*(4), 3625-3637.
19. Feng, D. C., Liu, Z. T., Wang, X. D., Chen, Y., Chang, J. Q., Wei, D. F., & Jiang, Z. M. (2020). Machine learning-based compressive strength prediction for concrete: An adaptive boosting approach. *Construction and Building Materials*, *230*, 117000.
20. Xu, M., Watanachaturaporn, P., Varshney, P. K., & Arora, M. K. (2005). Decision tree regression for soft classification of remote sensing data. *Remote Sensing of Environment*, *97*(3), 322-336.
21. Breiman, L. (2001). Random forests. *Machine learning*, *45*, 5-32.
22. Drucker, H., Burges, C. J., Kaufman, L., Smola, A., & Vapnik, V. (1996). Support vector regression machines. *Advances in neural information processing systems*, *9*.