Predicting elastic modulus of steel fibre-reinforced self-compacting concrete using hybrid machine learning models

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Abstract. Due to its outstanding fresh state performance, the self-compacting concrete (SCC) has been used in many applications such as sections with complex reinforcement and high-rise shear walls. To enhance mechanical properties and durability, steel fibres are introduced in SCC mixes. The fibre volume fraction and its geometrical parameters have been proven to have a significant impact on the elastic modulus, which is an important parameter for structural design. This study aims to implement machine learning techniques for predicting the elastic modulus of steel fibre-reinforced self-compacting concrete (SFRSCC). For this purpose, different machine learning models were developed. The performance of all models developed for predicting elastic modulus was evaluated and compared. The hybrid model demonstrated remarkable potential in predicting the elastic modulus of SFRSCC.

Keywords: self-compacting concrete; steel fibre reinforced concrete; elastic modulus; machine learning; mechanical properties

1. Introduction

Self-compacting concrete (SCC) was first proposed by Okamura and has gained wide acceptance in the construction industry (Okamura & Ozawa, 1996). SCC is characterised by its outstanding flowability and filling ability without any external vibrations. SCC can also achieve the desired level of viscosity without segregation and bleeding. However, SCC has poor resistance to cracking and shrinkage (Ahari et al., 2015). To address this issue, the incorporation of steel fibres, known for their superior bending and tensile toughness, can effectively enhance the mechanical properties of SCC. Consequently, it is crucial to determine the mechanical properties of steel fibre-reinforced self-compacting concrete (SFRSCC) in comparison to conventional SCC in order to satisfy concrete design requirements.

The elastic modulus is a crucial parameter for concrete analysis and structural design. Recommended values for the elastic modulus of SCC are provided in relevant standards and design guidelines (ACI Committee 318, 2007; NZS 3101, 2006; CSA, 2004). Furthermore, various design expressions describing the elastic modulus of SCC predominantly rely on compressive strength (Leemann & Hoffmann, 2005; Felekoğlu et al., 2007). In the research reported in (Khaliq & Kodur, 2011), SCC mixes were reinforced using three distinct fibre types. Mechanical test results demonstrated that the incorporation of steel fibres resulted in increased tensile strength and elastic modulus at elevated temperatures. However, in contrary it was also reported that SFRSCC had yielded a lower elastic modulus compared to normal concrete with the same compressive strength. This observation can be attributed to the significant influence of aggregate content and steel fibre properties on SFRSCC.

The elastic modulus of SFRSCC is influenced by numerous parameters, including not only the composition of SCC and testing conditions but also the shape, aspect ratio, and volume fraction of steel fibres. Consequently, it is difficult to predict the elastic modulus of SFRSCC by utilizing conventional statistical and modelling analysis. In this study, machine learning techniques were proposed for the first time to predict the elastic modulus of SFRSCC while accounting for complex interdependent factors. The workflow of this study is summarized in Figure 1.

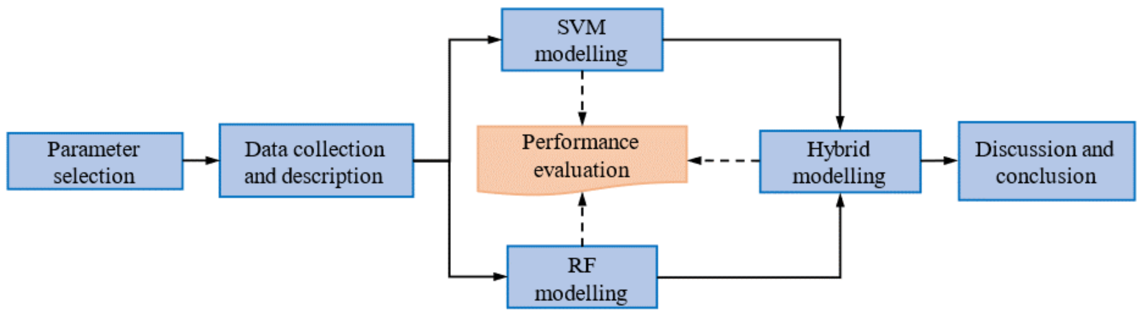


Figure 1: Flowchart of machine learning based prediction on elastic modulus of SFRSCC

2. Datasets and Evaluation Criteria

A comprehensive dataset is essential for training and validating machine learning models. In this study, datasets were compiled from the literature, encompassing experimental and simulated results from 19 published articles (Cunha et al., 2008; Pereira et al., 2008; Corinaldesi & Moriconi, 2011; Gencel et al., 2011; Aslani & Nejadi, 2013; AL-Ameeri, 2013; Frazão et al., 2015; Madandoust et al., 2015; Yehia et al., 2016; Rana T. Abdulkareem et al., 2016; da Silva et al., 2017; Ding et al., 2018; de Alencar Monteiro et al., 2018; Ghasemi et al., 2018; Mahmod et al., 2018; Ghasemi et al., 2019; Vijaya Kumar et al., 2020; Ouedraogo et al., 2021; Li et al., 2021). The components of SFRSCC and characteristics of main variables are selected as input variables, including cement to binder ratio (C/B), water to binder ratio (W/B), fine aggregate to coarse aggregate ratio (FA/CA), maximum size of coarse aggregate (AS), dosage of superplasticizers (SP), volume fraction of steel fibres (VFS), aspect ratio of steel fibres (ARS), tensile strength of steel fibres (TSS), curing age (Age), and compressive strength (Fcu). The sole output of models is the elastic modulus (EM) of SFRSCC. Moreover, 80% and 20% of the datasets were randomly selected as the training and testing sets, respectively. The statistical description of the dataset is presented in Table 1, while the distribution of all variables is shown in Figure 2. The dataset for each variable demonstrates a normal distribution pattern. Additionally, it can be observed that the compressive strength of the mixes has a strong positive impact on the elastic modulus, which aligns well with most findings reported in the literature.

The performance of developed models on training and testing datasets was assessed using three metrics, which are correlation coefficient (R^2), root mean square error (RMSE), and mean absolute error (MAE). It should be noticed that R^2 is dimensionless, while the unit of RMSE and MAE is GPa, same as that of elastic modulus.

Table 1: Descriptive analysis of all variables

Variable	Symbol	Unit	Mean	Minimum	Maximum	Standard Deviation

Cement to binder ratio	C/B	-	0.69	0.40	1.00	0.13
Water to binder ratio	W/B	-	0.34	0.13	0.52	0.08
Fine to coarse aggregate ratio	FA/CA	-	1.30	0.79	2.57	0.32
Maximum size of coarse aggregate	AS	mm	13.77	9.50	20.00	4.08
Dosage of superplasticizers	SP	%	1.20	0.44	6.00	0.90
Volume fraction of steel fibres	VFS	%	0.65	0.10	2.00	0.37
Aspect ratio of steel fibres	ARS	-	59.51	28.50	80.00	14.45
Tensile strength of steel fibres	TSS	MPa	1209.21	450.00	2800.00	313.43
Curing age	Age	Day	30.57	3.00	91.00	18.38
Compressive strength	Fcu	MPa	43.52	18.50	80.90	16.88
Elastic modulus	EM	GPa	31.68	18.08	49.50	6.01

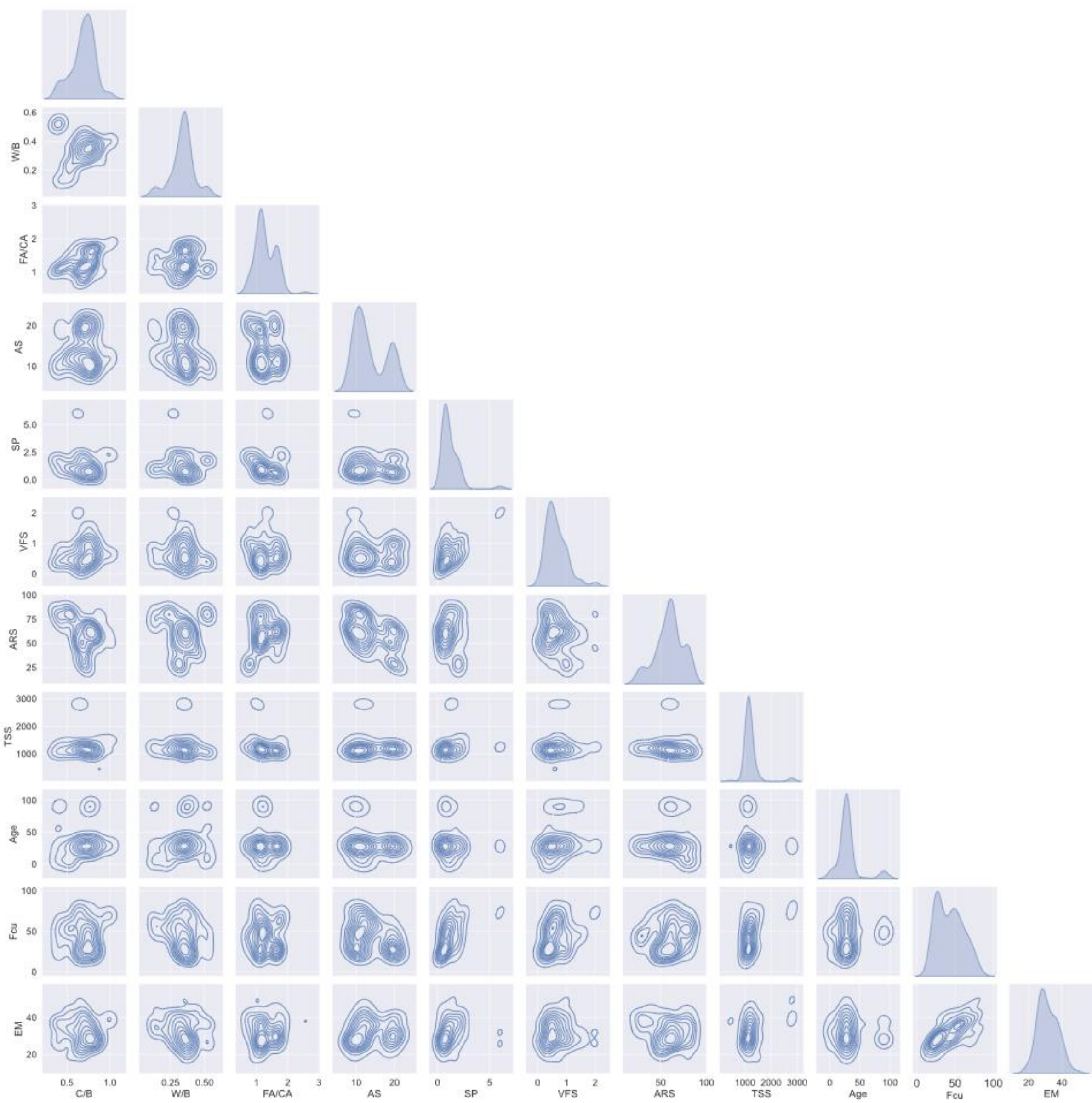


Figure 2: The relationship and distribution of all variables

3. Results and Discussion

In this section, machine learning algorithms are trained and tested using the assembled datasets. Support Vector Machine (SVM), Random Forest (RF), and the hybrid model are developed employing Python and relevant software libraries. The predictive performance of each model is evaluated and compared.

3.1 Development on Single Models

The Support Vector Machine (SVM) is developed based on statistical learning theory. The learning algorithm is configured using the geometric distance, taking into account the Vapnik-Chervonenkis dimension theory and the principle of structural risk minimization (Hsu et al., 2003). Due to its unique advantages in addressing small samples, high-dimensional data, and nonlinear problems, researchers have applied the SVM model forecasting to solve engineering challenges. To prevent overfitting and to enhance the reliability of models, 10-fold cross-validation was conducted prior to model training. Nine folds were selected as training datasets, while the remaining fold was used as the testing set. This process was repeated ten times, ensuring that each fold was selected at least once for testing. The mean values of metrics were then calculated for evaluating the developed models.

To circumvent issues arising from different units and scales of variables, all data were rescaled to a range between 0 to 1. To examine the predictive performance of different kernel function, four functions consisting of liner, polynomial, RBF and sigmoid were selected and compared. As given in Table 2, the RBF function yielded the best results in the initial SVM model, with the highest R^2 of 0.81 and lowest error values. Subsequently, the grid search was employed to determine the optimal combination of parameters C and Gamma, which represent the tolerance of error and mapped dimensions, respectively (Sánchez, 2003). The contour map of parameter pairs is shown in Figure 3, where the scores are represented by negative MAE values. It is evident that the maximum score is obtained when C and Gamma are 32 and 0.5 respectively.

Table 2: Performance of initial SVM models with different kernel functions

Kernel function	Statistical parameters		
	R^2	RMSE	MAE
Linear SVR	0.7221	3.0000	2.6140
Poly SVR	0.7414	2.8936	2.2785
RBF SVR	0.8108	2.4749	2.0342
Sigmoid SVR	-26.2330	29.6955	24.5170

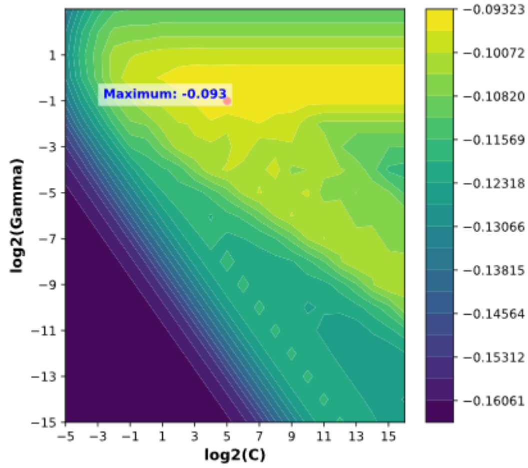


Figure 3: Grid search on parameter combinations of the SVR model

Random forest (RF) is a logic-based machine learning method that utilizes expressions and logical operations in a top-down approach. It achieves a comparable error rate to other methods for most learning tasks and exhibits a reduced tendency to overfit (Farooq et al., 2020). Notably, normalization of the datasets is not required for this method because it relies on hierarchical structures and branching logic rather than distance or gradient-based calculations, rendering it insensitive to the scale of input features. Several hyperparameters were considered during the tuning process, including maximum depth, minimum sample leaves, and minimum impurity decrease, among others. It was observed that the predictive performance enhancement, due to the tuning process, resulted in an increase of R^2 from 0.8619 to 0.9073 for the testing dataset.

Following the grid search and hyperparameter tuning, the developed SVM and RF models were employed to predict the elastic modulus of SFRSCC, as displayed in Figures 4 and 5. The minor discrepancies between the predicted and actual EM values indicate high prediction accuracy of proposed models for both training and testing datasets. The correlation coefficients for the testing sets of SVM and RF models are 0.8505 and 0.9073, respectively.

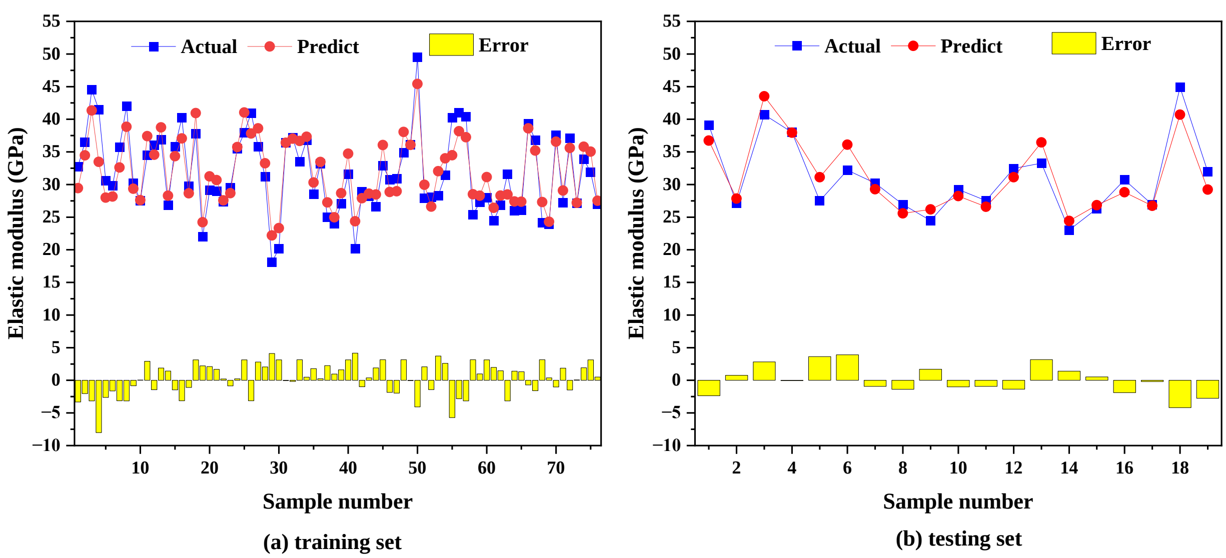
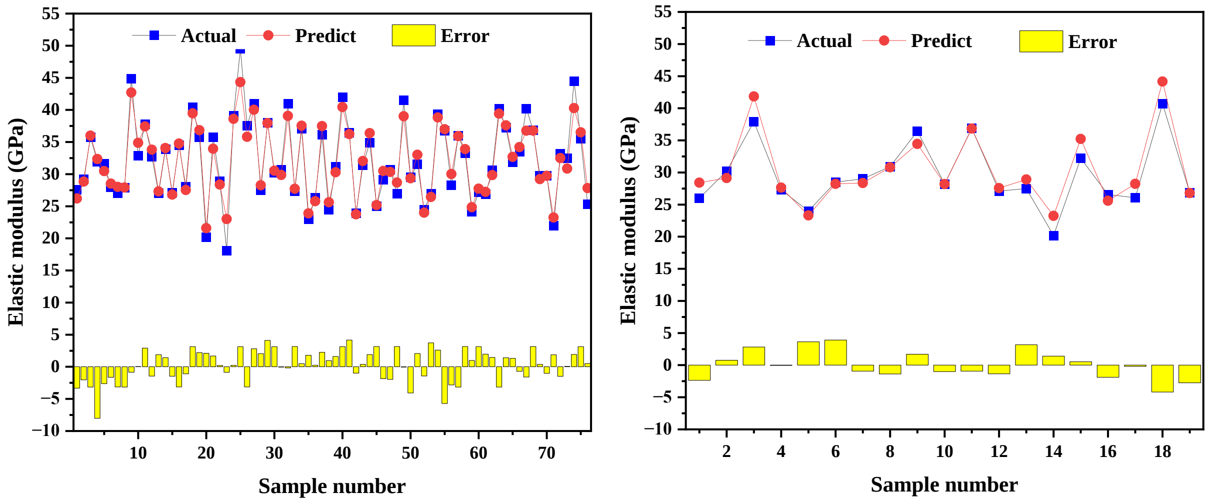


Figure 4: Comparison of prediction and actual elastic modulus of the SVM model



(a) training set

(b) testing set

Figure 5: Comparison of prediction and actual elastic modulus of the RF model

3.2 Development on the Hybrid Ensemble Model

In general, ensemble models can integrate multiple learning models to achieve superior performance compared to individual learning algorithms. A robust model can be developed by using various ensemble techniques, such as bagging, boosting and stacking. The RF was selected to construct the proposed hybrid model, which aggregates the outputs of individual models as new inputs and the experimental EM values as the final output dataset. Consequently, the hybrid model consists of two input variables and a single output variable. Figure 6 shows the performance of the hybrid model on both training and testing sets. It can be observed that the hybrid model attained a narrower interquartile range of the error box, indicating that the majority of errors produced by the hybrid model were more concentrated than those generated by the SVM and RF models.

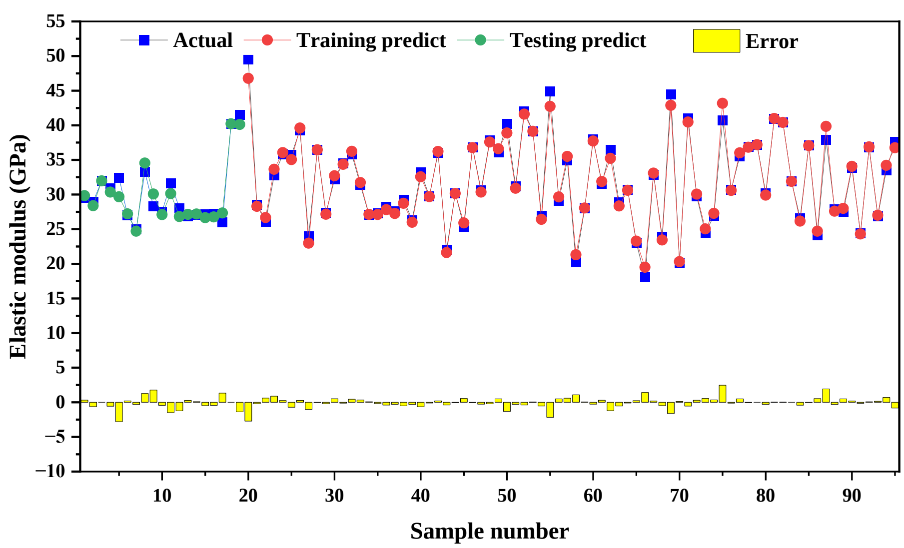


Figure 6: Comparison of prediction and actual elastic modulus of the hybrid model

The prediction accuracy of single models and the hybrid model is illustrated in Table 3. The high correlation coefficient on the testing set (0.9429) demonstrates the enhanced predictive capability of the proposed hybrid model. Additionally, lower MAE and RMSE values suggest the absence of overfitting. Furthermore, the linear relationships between the actual and predicted EM values were assessed for all models using scatter plots, as depicted in Figure 7. In comparison with single models, the proposed hybrid model displays more scatters distributed closer to the diagonal, which indicates a superior fitting ability.

Table 3: Prediction accuracy of machine learning models

	R^2	RMSE	MAE
SVM	0.8505	1.8383	2.2107
RF	0.9073	1.3745	1.8610
Hybrid	0.9429	0.7881	1.0637

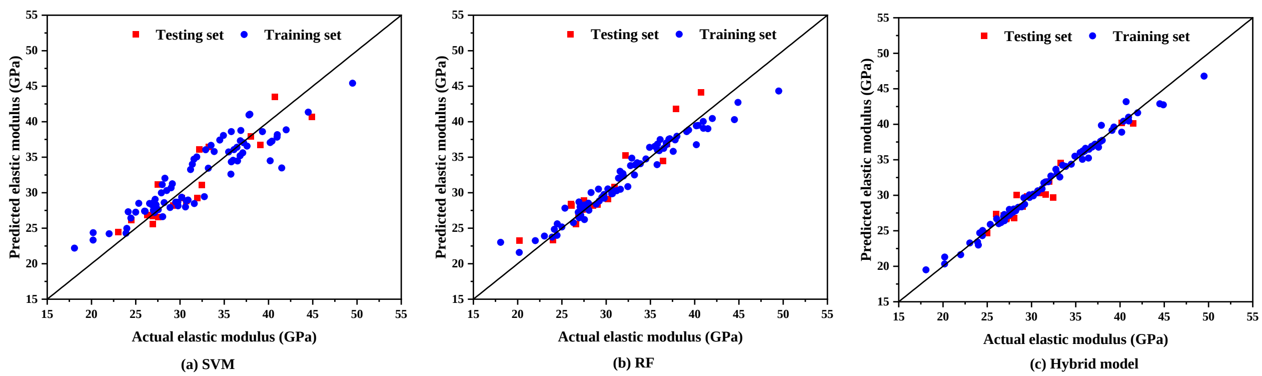


Figure 7: Illustration of regression plot between actual and predicted value of EM

4. Conclusion

This study presents an innovative and comprehensive approach to predict the elastic modulus of steel fibre-reinforced self-compacting concrete (SFRSCC) using hybrid machine learning models. The investigation involved the development and comparison of individual Support Vector Machine (SVM) and Random Forest (RF) models, followed by the introduction of a hybrid model that leveraged the strengths of both techniques. Both individual SVM and RF models demonstrated satisfactory prediction accuracy, with correlation coefficients of 0.8505 and 0.9073 for the testing sets, respectively. The hybrid model, which integrated the outputs of SVM and RF models, achieved a superior performance with a correlation coefficient of 0.9429 on the testing set, alongside lower MAE and RMSE values, indicating its enhanced predictive capability and absence of overfitting.

The findings of this study emphasize the potential of employing hybrid machine learning models for predicting the elastic modulus of SFRSCC, considering the complex relationships between various input variables. The proposed hybrid model offers a valuable tool for researchers and practitioners in the field of civil engineering, enabling efficient and reliable design and analysis of SFRSCC structures. Future studies may consider extending the application of the hybrid model to other SFRSCC properties and to investigate the incorporation of additional input variables along with expanding the dataset scale to further enhance prediction accuracy.

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