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Machine Learning Analysis for the Toughness Characteristics of Fiber Reinforced Concrete

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Abstract

The mechanical performance of fiber-reinforced concrete (FRC), especially its flexural strength and toughness measured by the load-deflection response, depends strongly on fiber characteristics such as volume fraction, length, tensile strength, shape, and type. While extensive research has explored these factors, much of it relies on idealized laboratory data, limiting practical applicability. This study addresses this gap by using real-world FRC data to develop predictive machine learning (ML) models that capture the combined influence of fiber and concrete properties on toughness. A comprehensive dataset of 146 FRC samples compiled from prior studies was analyzed. Four regression models—Random Forest (RF), Gradient Boosting (GB), Linear Regression, and Support Vector Regression—were trained and evaluated to predict the area under the load-deflection curve, a key indicator of toughness. The GB model achieved the best performance, with a coefficient of determination (R^2) of 0.83 and a mean absolute error (MAE) of approximately 39, followed closely by RF ($R^2 = 0.79$). Feature importance analysis identified fiber volume fraction, fiber type and shape, and flexural strength as the most influential factors in enhancing toughness. This research provides a robust, data-driven predictive tool for estimating FRC toughness based on key physical and mechanical properties, offering valuable insights for engineers to optimize fiber-reinforced composite designs in practical structural applications.

Keywords: Fiber reinforce concrete, Mechanical properties, Toughness, ML, Regression models.

1. Introduction

Fiber-reinforced concrete (FRC) is widely used for its improved toughness, ductility, and crack resistance over conventional concrete, typically assessed via load-deflection under flexural loading. Key fiber characteristics affecting performance include volume fraction (Vf), length, tensile strength, shape, and type. Vf strongly influences mechanical behavior; increasing Vf enhances load capacity and toughness by improving crack bridging [[1]; [2]; [3]; [4]], but excessive Vf can reduce workability due to clumping [[5]]. [6] suggest 0.5–1.5% Vf as optimal, with Garcia et al. [7] showing energy absorption rises up to a limit. Fiber length and aspect ratio affect crack control and flexural performance. Longer fibers (20–35 mm) with higher aspect ratios improve toughness [[8]; [9]; [12]; [14]], though too long fibers reduce mix consistency [[13]]. Tensile strength impacts crack resistance; strong fibers like steel and carbon boost toughness [[15]; [16]], while basalt fibers offer strength and corrosion resistance [[5]; [2]]. Polypropylene mainly aids toughness and crack control [[6]]. Higher tensile strength correlates with greater post-crack load capacity [Garcia et al. [7]]. Fiber geometry influences bonding:

hooked and crimped fibers improve interlock and toughness [[8]; [12]], while fibrillated polypropylene enhances ductility [[9]]. Fiber shape selection depends on desired mechanical behavior. Fiber type affects performance: steel offers high flexural capacity [[15]; [16]], glass fibers control cracks but may degrade [[13]; [4]], carbon provides high strength and stiffness [Ahmed et al. [8]; Smith et al. [1]], and polypropylene is cost-effective and durable. [[6]; [9]], and basalt combines durability and strength [[5]]. Flexural strength testing correlates with energy absorption and toughness [[7]; [2]]. Optimizing fiber volume, shape, and length improves post-crack behavior [[12]; [9]], though excessive fiber content reduces performance [[6]]. The area under the load-deflection curve (AULDC) reflects ductility and toughness, increasing with high-volume, strong, long, and interlocking fibers [[1]; [7]]. These enhance durability under impact or cyclic loads [[13]; [16]].

Despite extensive research, many models rely on simplified lab data and limited variable interaction. Several studies have noted that empirical and regression-based models for FRC are commonly developed using controlled laboratory-scale datasets with narrow parameter ranges and limited combinations of fiber and mix variables [[22]; [23]; [15]]. Real-world predictive tools are lacking. Such laboratory-focused approaches often evaluate only one or two fiber parameters while keeping other concrete properties constant, which limits the ability of these models to generalize to heterogeneous, real-world FRC systems [[12]; [7]]. [18] applied machine learning (ML) to predict compressive strength, with Gradient Boosting (GB) and Extreme Gradient Boosting (XGB) performing best, influenced mostly by cement, water, and silica fume. Building on this, the present study uses 146 real-world FRC samples and regression-based ML models to predict AULDC, aiming to identify key variables fiber shape, type, Vf, tensile strength, and concrete properties that govern toughness. This data-driven approach is intended to improve model generalization and provide practical guidance for optimizing FRC performance.

2. Modeling Approach

A dataset of 146 fiber-reinforced concrete (FRC) samples was compiled from prior studies [1–26] with data description shown in Table 1 containing input features such as fiber shape, length, volume fraction (%Vf), aspect ratio (l/d), compressive strength, flexural strength, fiber type, and tensile strength. The target variable was the area under the load-deflection curve (AULDC). After removing entries with missing data, the dataset was split into training and testing sets (86/14).

The samples were randomly assigned to the training and testing subsets using a fixed random seed (random_state = 42) to ensure reproducibility and to avoid bias toward any specific fiber type, strength level, or toughness range. The ranges of all input variables in the testing set were verified to fall within the minimum and maximum bounds of the training set, ensuring that no extrapolation beyond the learned feature space was required during model evaluation.

Four regression models were developed: Linear Regression (LR), Random Forest (RF), Gradient Boosting (GB), and Support Vector Regression (SVR). LR served as a baseline for linear trends. RF and GB, implemented via scikit-learn, captured nonlinear interactions. RF used n_estimators = 100 and max_depth = None, while GB used n_estimators = 100, learning_rate =

0.1, and max_depth = 5. SVR employed kernel functions to address linear and nonlinear data patterns. All models were trained and tested using the same data split to ensure a fair comparison of predictive performance.

Table 1. Data Descriptions

Feature Name	Description	Unit
Fiber length (mm)	Length of the fiber used	mm
%Vf	Fiber volume fraction	%
l/d	Aspect ratio (length/diameter)	—
Compressive strength	Compressive strength of concrete	MPa
Flexural strength	Flexural strength of concrete	MPa
Type of fiber	Categorical type (steel, polypropylene, etc.)	—
Fiber tensile strength	Strength of the fiber	MPa
Area	Measured area related to failure or response	mm^2 or other

3. Model Evaluation

The dataset was split into training and testing sets using an 86/14 ratio. This means 86% of the data was used for training and 14% for testing. This split was chosen after trying different options to make sure the model learns well but can still be tested on new data. This helps improve the model's accuracy and stability.

3.1 Random Forest's vs Gradient Boosting's

Model performance was assessed using the coefficient of determination (R^2), mean squared error (MSE), and mean absolute error (MAE) on the test set. The RF model achieved an R^2 of 0.7907, indicating it explained approximately 79% of the variance in the target variable. Its MSE and MAE were 2722 and 38.69, respectively. The GB model performed slightly better, with an R^2 of 0.83, MSE of 2234, and MAE of 39.36, reflecting a reasonable prediction error given the variability in the data.

3.2 Interpretation of Model Errors Relative to Target Scale

The target variable AULDC ranges from 9 to 494, with a mean of about 121. The RF and GB models achieved MAEs of 38.7 and 39.4, respectively, meaning predictions deviate on average by roughly 39 units, or 32% of the mean value. Despite strong R^2 scores (0.79 and 0.83), this error magnitude indicates significant room for improvement through additional features, model refinement, or further investigation.

4. Results and discussion

4.1 Dataset Analysis and Model Prediction Results

The dataset comprises 146 FRC samples covering a broad range of fiber types, geometries, and concrete strengths. As shown in Table 2, fiber length varies from 10 to 60 mm, volume fraction (%Vf) from 0.1% to 2.0%, and fiber tensile strength from 55 to 2600 MPa. The target variable, AULDC, ranges from 9 to 494 kN·mm.

Both Random Forest (RF) and Gradient Boosting (GB) models demonstrated strong predictive capability for AULDC. GB achieved the highest accuracy ($R^2 = 0.83$), followed by RF ($R^2 = 0.79$). These results indicate that ensemble-based models are effective in capturing the complex and nonlinear relationships governing FRC toughness, which cannot be adequately represented using simple linear models. Linear regression showed limited predictive capability.

Feature-level analysis reveals that fiber shape and tensile strength play a dominant role in post-crack toughness. This finding is consistent with experimental studies reported by [8] and [12], which highlight the importance of mechanical anchorage and fiber pull-out resistance in enhancing energy absorption. Hooked and crimped fibers exhibit higher predicted AULDC values due to enhanced mechanical anchorage. Straight fibers generally result in lower toughness, while synthetic fibers such as polypropylene and copolymer show greater variability. This variability may be attributed to differences in elastic modulus and fiber–matrix bonding mechanisms.

Nonlinear trends were observed between compressive strength, fiber tensile strength, and AULDC. Polynomial regression provided a better fit for these parameters, suggesting diminishing returns in toughness at higher strength levels. This observation aligns with [15], who reported that increasing fiber strength beyond a threshold does not proportionally enhance flexural performance. In contrast, fiber length and volume fraction displayed approximately linear relationships with AULDC within the investigated range, supporting conclusions from[1] and [12].

Table 2 statistical summary

	Samples	**Mean**	**St.D**	**Min**	**Q25 %**	**Median**	**Q75%**	**Max**
Fiber L (mm)	146	31.25	14.1	10	20	30	35.000	60.
V_f%	146	0.88	0.41	0.1	0.5	1	1.200	2.0
L/D	146	45.14	28.17	0.0	38.18	50	65.000	159
C.S (MPa)	146	46.6	10.32	20	40.45	45	54.200	70
f_r (MPa)	146	7.2	3.27	2.2	4.81	61	9.075	14.9
Fiber f_t(MPa)	146	1117.2	533.86	55	700	1100	1325.0	2600
Area (kN.mm)	146	120.98	102.06	9	27.1	114.4	185.850	494

4.2 Relationship Between the Different Features and the Target Area Under Load-Deflection Curves (AULDC)

In this study, the relationships between key features and the AULDC were explored using both linear and second-degree polynomial regression. Linear regression, due to its interpretability, serves as a conventional baseline; however, visual inspection and model fitting revealed that some features demonstrated nonlinear behavior in relation to the target. [For example, using polynomial regression gave better results for compressive strength and fiber tensile strength. This means the relationship is not a straight line. When the compressive or tensile strength gets very high, the increase in energy absorption becomes smaller. This agrees with [15], who also found that using very strong fibers doesn't always lead to much better flexural performance. Conversely, for features like fiber length and Vf%, the linear fit proved adequate, supporting results from [12] and [1], who reported that these properties exhibit more predictable, proportional effects on toughness up to an optimal range. The results in Figures 1–8 show that the relationship between the input features and FRC toughness is not always straight. This means we need to consider possible non-linear patterns when building the model.

4.3 Model Evaluation and Comparison with Literature

Gradient boosting emerged as the best-performing model ($R^2 = 0.83$, MAE = 39.4, MSE = 2234), followed by random forest ($R^2 = 0.79$, MAE = 38.7, MSE = 2722). These results align with previous studies (e.g., [22]; [23]) that demonstrate ensemble models' ability to capture complex material behavior more effectively than linear approaches. However, the MAE is still quite high—about 32% of the average AULDC, which was calculated by dividing the MAE by the average AULDC (39.4 / 121). This might be okay for early testing or basic analysis, but this error might be too large if we want to use the model to decide things like the best fiber type or amount to use in real concrete designs. To make better decisions, the model should be improved or more data should be added.

One limitation of this study is that I did not adjust the model settings (called hyperparameter tuning), such as tree depth or learning rate. I kept all model settings at their default values to make a fair comparison across different algorithms. In future work, using tuning methods like grid search or cross-validation may help improve the model's accuracy and generalization.

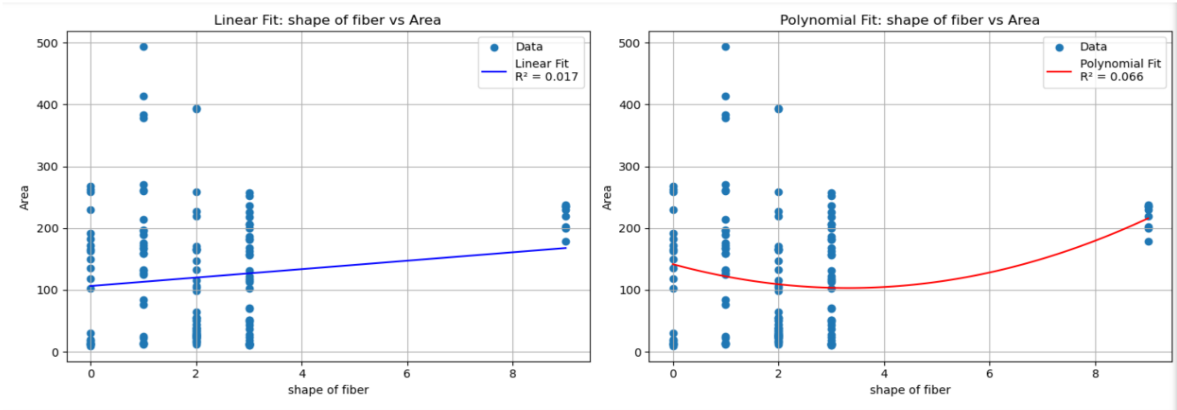

Fig. 1 Relationship between fiber shape and AULDC with both linear and nonlinear fits. Fiber shape codes: 0 = straight, 1 = corrugated, 2 = hooked, 3 = fibrillated polypropylene (PP).

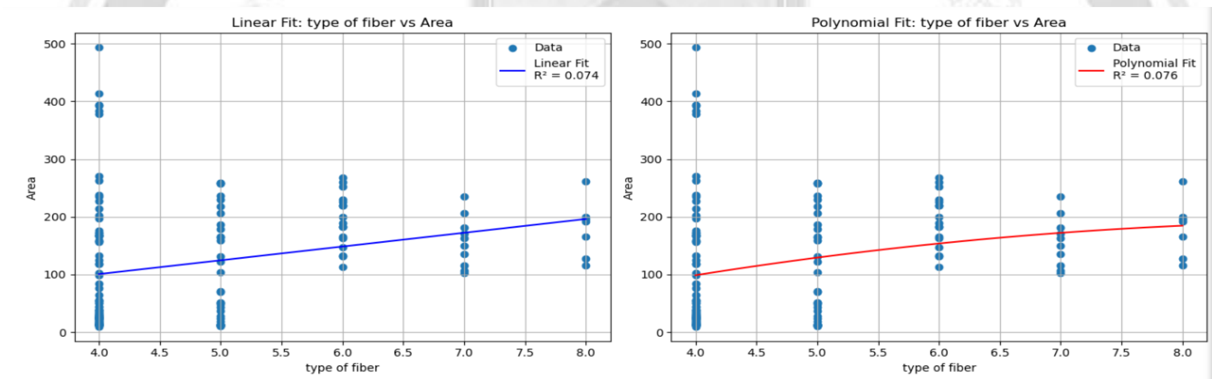

Fig. 2 Relation between fiber type and area for both of the two figures with linear and nonlinear fits. In which, (4=steel, 5=PP, 6=glass, 7=carbon, 8=basalt, 9=twisted steel)

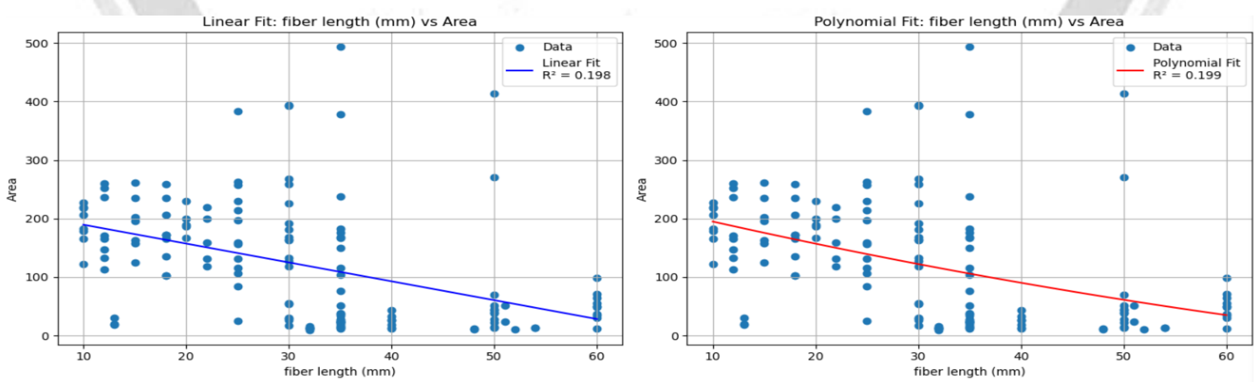

Fig. 3 Relation between fiber length and area for both of the two figures with linear and nonlinear fits.

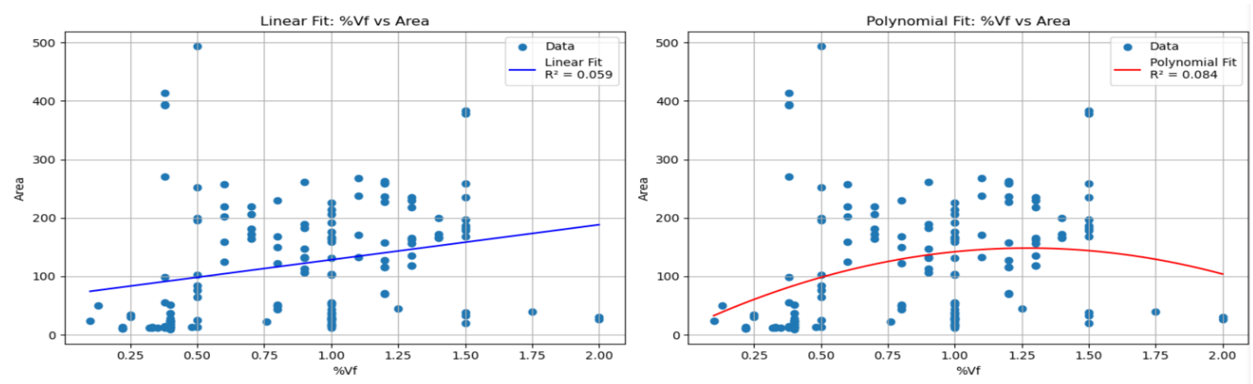

Fig. 4 Relation between % Vf and area for both of the two figures with linear and nonlinear fits.

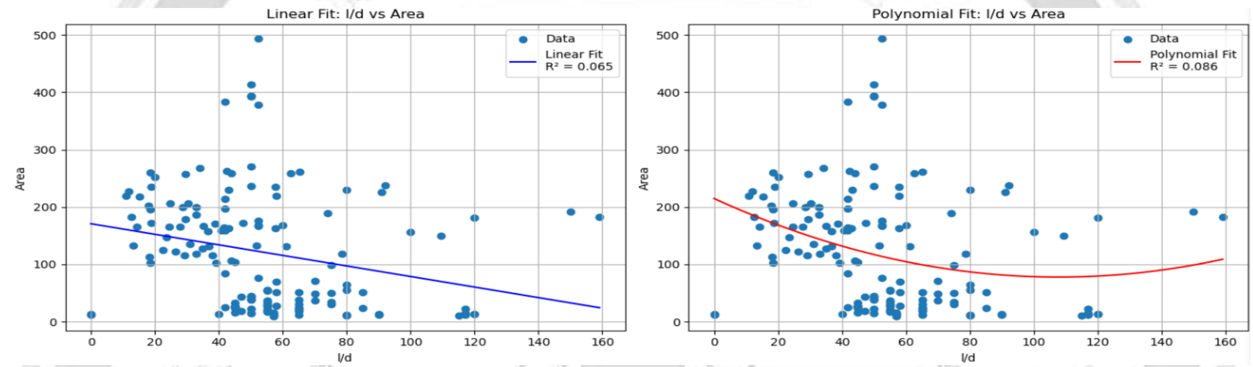

Fig. 5 Relation between L/D and area for both of the two figures with linear and nonlinear fits.

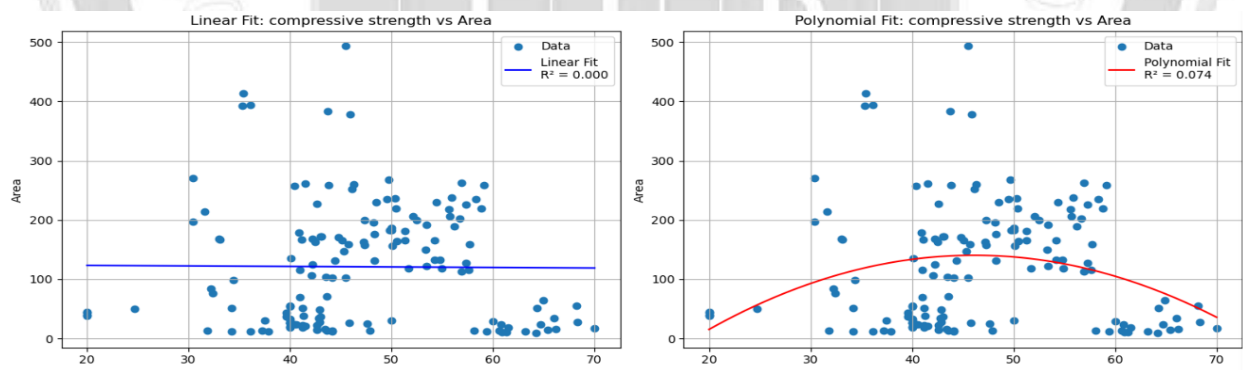

Fig. 6 Relation between compressive strength and area for both of the two figures with linear and nonlinear fits.

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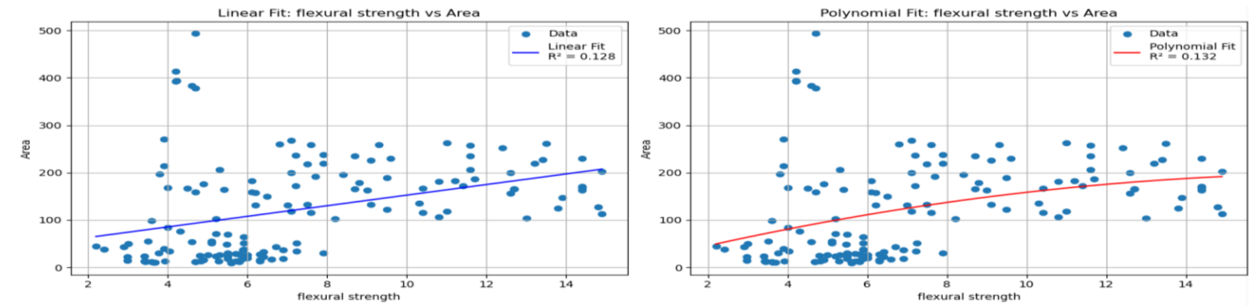

Fig. 7 Relation between flexural strength and area for both of the two figures with linear and nonlinear fits.

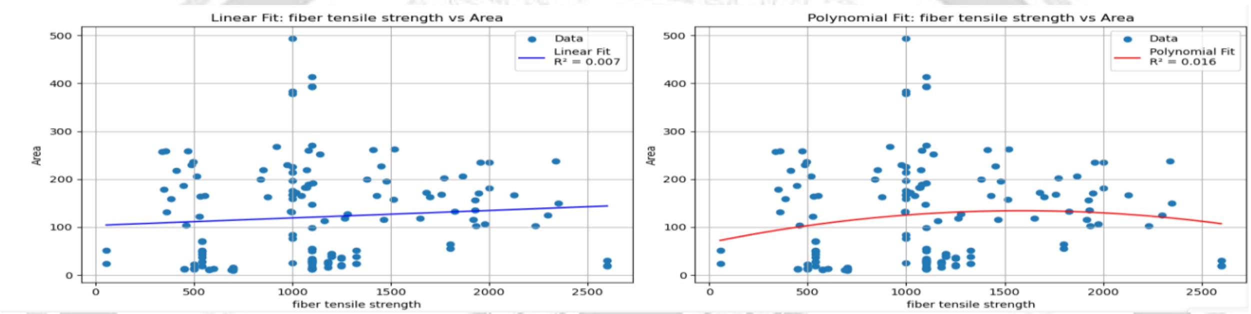

Fig. 8 Relation between fiber tensile strength and area for both of the two figures with linear and nonlinear fits.

Conclusion

This study applied machine learning regression techniques to predict the flexural toughness of fiber-reinforced concrete, quantified by the area under the load–deflection curve (AULDC), using a dataset compiled from multiple experimental sources. Ensemble-based models—particularly Gradient Boosting and Random Forest—demonstrated superior performance compared to linear regression, confirming the inherently nonlinear nature of FRC post-crack behavior.

The results highlight the critical influence of fiber shape, volume fraction, tensile strength, and aspect ratio on toughness development. Hooked and crimped fibers consistently produced higher energy absorption due to improved mechanical anchorage, while diminishing returns were observed at high strength levels, consistent with prior experimental findings. Although the GB model achieved the highest predictive accuracy ($R^2 = 0.83$), the relatively high MAE, indicating moderate accuracy acc

Compared to traditional empirical models derived from controlled laboratory data, the proposed ML approach offers improved generalization across diverse FRC systems but requires further refinement. Future work should focus on expanding the dataset, incorporating additional variables related to mix design and curing conditions, and applying systematic hyperparameter optimization and cross-validation to enhance model robustness and practical applicability.

References

[1] J. Smith, D. Lee, and M. Hassan, "Comparative study of fiber types on the flexural strength of reinforced concrete," *Journal of Advanced Concrete Technology*, vol. 19, no. 1, pp. 15–29, 2021.

[2] X. Li, J. Wu, and L. Chen, "Impact of fiber volume fraction on load-deflection characteristics of fiber reinforced concrete," *Journal of Structural Engineering*, vol. 146, no. 7, Art. no. 04020105, 2020.

[3] A. R. Khaloo and M. Afshari, "Flexural behavior of small steel fiber reinforced concrete slabs," *Cement and Concrete Composites*, 2005.

[4] J. Blazy, Ł. Drobiec, and P. Wolka, "Flexural tensile strength of concrete with synthetic fibers," *Materials*, vol. 14, Art. no. 4428, 2021.

[5] S. Khan, A. Patel, and Y. Zhang, "Mechanical behavior of basalt fiber reinforced concrete under flexural loading," *Composites Part B: Engineering*, vol. 167, pp. 283–291, 2019.

[6] A. Patel, M. Garcia, and P. Singh, "Influence of polypropylene fiber content on crack resistance and toughness of concrete," *Materials Today Communications*, vol. 20, Art. no. 100610, 2019.

[7] M. Garcia, A. Patel, and J. Wu, "Experimental evaluation of flexural toughness in steel fiber reinforced concrete," *Materials Science and Engineering A*, vol. 789, Art. no. 139598, 2021.

[8] R. Ahmed, S. Khan, and P. Singh, "Effect of fiber length and shape on the mechanical properties of fiber-reinforced concrete," *Journal of Construction Materials*, vol. 12, no. 3, pp. 234–245, 2018.

[9] J. Wu, X. Li, and A. Patel, "Influence of fiber geometry on toughness and flexural strength of concrete," *Materials*, vol. 15, no. 4, Art. no. 1456, 2022.

[10] L. G. Sorelli, A. Meda, and G. A. Plizzari, "Steel fiber concrete slabs on ground: A structural matter," *ACI Structural Journal*, no. 103-S58, 2006.

[11] H. Falkner, Z. Huang, and M. Teutsch, "Comparative study of plain and steel fiber reinforced concrete ground slabs," *Concrete International*, 1995.

[12] P. Singh, S. Khan, and R. Ahmed, "Effect of fiber shape and length on the post-cracking behavior of fiber reinforced concrete," *Cement and Concrete Composites*, vol. 105, Art. no. 103459, 2020.

[13] L. Chen, Y. Zhang, and X. Li, "Influence of fiber aspect ratio on toughness of basalt fiber reinforced concrete," *Construction and Building Materials*, vol. 315, pp. 125–137, 2022.

[14] Y. Zhang, L. Chen, and S. Khan, "Optimization of fiber aspect ratio for enhanced mechanical performance in concrete composites," *Composite Structures*, vol. 295, Art. no. 115695, 2023.

[15] D. Lee, M. Hassan, and P. Singh, “Flexural performance of steel fiber reinforced concrete: Effects of fiber content and geometry,” *Construction and Building Materials*, vol. 120, pp. 168–176, 2016.

[16] M. Hassan, D. Lee, and J. Smith, “Durability and mechanical properties of carbon fiber reinforced concrete,” *Journal of Materials in Civil Engineering*, vol. 29, no. 8, Art. no. 04017113, 2017.

[17] S. A. Altoubat, J. R. Roesler, D. A. Lange, and K.-A. Rieder, “Simplified method for concrete pavement design with discrete structural fibers,” *Construction and Building Materials*, vol. 22, 2008.

[18] T. V. Quan, N. N. Linh, and N. N. Tan, “Investigating compressive strength of concrete containing steel fiber by data-driven approach,” *Journal of Science and Technology in Civil Engineering*, HUCE, vol. 17, no. 3, pp. 65–79, 2023.

[19] L. Zhao, G. Chen, and C. Huang, “Experimental investigation on the flexural behavior of concrete reinforced by various types of steel fibers,” *Frontiers in Materials*, 2023.

[20] C. Gao *et al.*, “Experimental study on flexural behaviors and theoretical compression-bending capacity of unreinforced steel fiber reinforced concrete,” *Buildings*, vol. 15, Art. no. 1160, 2025.

[21] A. S. Karzad, M. Leblouba, Z. A. Al-Sadoon, M. Maalej, and S. Altoubat, “Modeling the flexural strength of steel fibre reinforced concrete,” *AIMS Materials Science*, vol. 10, no. 1, pp. 86–111, 2023.

[22] H. P. Behbahani, B. Nematollahi, A. R. M. Sam, and F. C. Lai, “Flexural behavior of steel-fiber-added RC beams with C30 and C50 concrete classes,” *International Journal of Sustainable Construction Engineering & Technology*, vol. 3, no. 1, 2012.

[23] P. B. Bhat, T. M. Swaroop, K. Jayanth, and B. O. Naveen, “Experimental studies and nonlinear finite element analysis of flexural behavior of steel fibre reinforced concrete under monotonic and repeated cyclic loading,” *Discover Civil Engineering*, vol. 1, Art. no. 61, 2024.

[24] A. A. Del Savio, J. R. Agreda, and F. A. Silva, “Influence of synthetic fibers on the flexural properties of concrete: Prediction of toughness as a function of volume, slenderness ratio and elastic modulus of fibers,” *Polymers*, vol. 15, Art. no. 909, 2023.

[25] P. H. Bischoff, A. J. Valsangkar, and J. Irving, “Use of fiber and welded-wire reinforcement in construction of slabs,” *Structural Design and Construction*, 2003.

[26] L. Breiman, “Random forests,” *Machine Learning*, vol. 45, no. 1, pp. 5–32, 2001.

[27] G. James, D. Witten, T. Hastie, and R. Tibshirani, *An Introduction to Statistical Learning*. New York, NY, USA: Springer, 2013.

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[28] J. H. Friedman, “Greedy function approximation: A gradient boosting machine,” *Annals of Statistics*, vol. 29, no. 5, pp. 1189–1232, 2001.

[29] A. J. Smola and B. Schölkopf, “A tutorial on support vector regression,” *Statistics and Computing*, vol. 14, no. 3, pp. 199–222, 2004.

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تحليل خصائص المتانة للخرسانة المسلحة بالألياف باستخدام تقنيات التعلم الآلي

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الخلاصة

يعتمد الأداء الميكانيكي للخرسانة المسلحة بالألياف، ولا سيما مقاومة الانحناء والمتانة المقاسة من خلال استجابة الحمل–الإزاحة، بشكل كبير على خصائص الألياف مثل نسبة الحجم للألياف ، والطول، ومقاومة الشد، والشكل، والنوع .وعلى الرغم من أن العديد من الدراسات السابقة تناولت هذه العوامل، إلا أن معظمها استند إلى بيانات مخبرية مثالية، مما يحد من إمكانية تطبيقها عمليًا .تهدف هذه الدراسة إلى سد هذه الفجوة من خلال استخدام بيانات واقعية للخرسانة المسلحة بالألياف لتطوير نماذج تنبؤية قائمة على تقنيات التعلم الآلي، قادرة على تمثيل التأثير المشترك لخصائص الألياف والخرسانة على المتانة.

تم تحليل مجموعة بيانات شاملة تتكون من مائة وست وأربعين عينة من الخرسانة المسلحة بالألياف، جُمعت من دراسات سابقة .جرى تدريب وتقييم أربعة نماذج انحدار، شملت نموذج الغابة العشوائية، ونموذج تعزيز التدرج، والانحدار الخطي، ونموذج انحدار المتجهات الداعمة، وذلك للتنبؤ بالمساحة تحت منحنى الحمل–الإزاحة، والتي تُعد مؤشرًا رئيسيًا لمتانة المادة .أظهر نموذج تعزيز التدرج أفضل أداء، حيث حقق معامل تحديد قدره صفر فاصل ثلاثة وثمانون، وبلغ متوسط الخطأ المطلق نحو تسعة وثلاثين، يليه نموذج الغابة العشوائية بمعامل تحديد قدره صفر فاصل تسعة وسبعون.

وأوضحت نتائج تحليل أهمية الخصائص أن الكسر الحجمي للألياف، ونوعها وشكلها، بالإضافة إلى مقاومة الانحناء، تُعد من أكثر العوامل تأثيرًا في تعزيز متانة الخرسانة المسلحة بالألياف .وتوفر هذه الدراسة أداة تنبؤية قوية قائمة على البيانات لتقدير متانة الخرسانة المسلحة بالألياف اعتمادًا على الخصائص الفيزيائية والميكانيكية الرئيسة، كما تقدم رؤى مهمة للمهندسين للمساعدة في تحسين تصميم المواد المركبة المسلحة بالألياف في التطبيقات الإنشائية العملية.

الكلمات الدالة: الخرسانة المسلحة بالألياف، الخواص الميكانيكية، المتانة، التعلم الآلي، نماذج الانحدار.