Iğdır Üniversitesi Fen Bilimleri Enstitüsü Dergisi, 15(2), 568-580, 2025
Journal of the Institute of Science and Technology, 15(2), 568-580, 2025
ISSN: 2146-0574, eISSN: 2536-4618
İnşaat Mühendisliği / *Civil Engineering* **DOI: 10.21597/jist.1584930**
Araştırma Makalesi / *Research Article*
Geliş tarihi / *Received*: 13.11.2024 **Kabul tarihi / *Accepted*: 05.02.2025**
Atıf İçin: Kurtoğlu, A.E. (2025). PVC İle Sargılanmış Betonun Eksenel Basınç Dayanımının Makine Öğrenmesi İle Tahmini. *Iğdır Üniversitesi Fen Bilimleri Enstitüsü Dergisi*, 15(2), 568-580.
To Cite: Kurtoğlu, A.E. (2025). Predicting the Compressive Strength of PVC-Confined Concrete via Machine Learning . *Journal of the Institute of Science and Technology*, 15(2), 568-580.

PVC İle Sargılanmış Betonun Eksenel Basınç Dayanımının Makine Öğrenmesi İle Tahmini

Ahmet Emin KURTOĞLU[1*]

Öne Çıkanlar:
- Sürdürülebilir malzeme avantajı
- Üstün tahmin kapasiteli makine öğrenmesi modelleri
- Karmaşık parametre ilişkilerinin tespiti

Anahtar Kelimeler:
- Sargılanmış beton
- Basınç dayanımı
- PVC
- Makine öğrenmesi
- Sonlu elemanlar analizi

ÖZET:

Polivinil Klorür (PVC), korozyon direnci, dayanıklılığı ve maliyet etkinliği sayesinde betonun yapı uygulamalarında sargılanması için geleneksel malzemelere bir alternatif olma potansiyeline sahip sürdürülebilir bir seçenektir. Bu araştırma, PVC ile sargılanmış beton kısa kolonların eksenel basınç dayanımı üzerine yoğunlaşmakta ve yüksek tahmin kapasiteli makine öğrenimi modelleri kullanılmaktadır. Sonlu Elemanlar Analizi (FEA) simülasyonlarından elde edilen bir veri tabanı kullanılarak, Yapay Sinir Ağı (YSA) ve Destek Vektör Makinesi (DVM) modelleri eğitilmiştir ve her modelin performansı mevcut bir ampirik modelle karşılaştırılmıştır. YSA ve DVM modelleri, 1.0'a yakın R^2 değerleri ve geleneksel ampirik yaklaşımlara kıyasla daha düşük RMSE değerleri ile yüksek tahmin doğruluğu elde edebilmiştir. Sonuçlar, makine öğrenimi modellerinin, PVC kalınlığı, kolon çapı ve beton basınç dayanımı gibi parametreler arasındaki karmaşık etkileşimleri başarılı bir şekilde yakalayarak dayanım tahmini için esnek ve güçlü bir yöntem sağladığını göstermiştir. Bu modeller, inşaat mühendislerine kapsamlı fiziksel testlere gerek kalmadan PVC ile sargılanmış beton kolon mukavemetlerini tahmin etmek için hızlı ve uygun maliyetli bir araç sunarak yapısal tasarımda sürdürülebilir malzemelerin benimsenmesini potansiyel olarak hızlandırmaktadır. Bu yaklaşım, deneysel maliyetleri ve tasarım süresini azaltarak yenilikçi inşaat teknolojileri için önemli bir pratik değer ortaya koymaktadır.

Predicting the Compressive Strength of PVC-Confined Concrete via Machine Learning

Highlights:
- Sustainable Material Advantage
- Machine learning models with superior predictive capacity
- Detection of complex parameter relationships

Keywords:
- Confined concrete
- Compressive strength
- PVC
- Machine learning
- Finite element analysis

ABSTRACT:

Polyvinyl Chloride (PVC) is a promising sustainable alternative to traditional materials for confining concrete in structural applications due to its corrosion resistance, durability, and cost-effectiveness. The present research is focused on the axial compressive strength of PVC-confined concrete short columns with machine learning models for superior predictive accuracy. A database gathered from FEA simulations was utilized to train the Artificial Neural Network (ANN) and Support Vector Machine (SVM) models, in which the performance of each model was compared with an available empirical formula. The ANN and SVM models could achieve a high predictive accuracy with R^2 values close to 1.0 and smaller RMSE values than those by traditional empirical approaches. Results have shown that machine-learning models succeed in capturing complex interactions among the parameters, including PVC thickness, column diameter, and concrete compressive strength, providing a versatile and powerful method for strength prediction. These models offer construction engineers a rapid, cost-effective tool for predicting PVC-confined concrete column strengths without extensive physical testing, potentially accelerating the adoption of sustainable materials in structural design. By reducing experimental costs and design time, the approach demonstrates significant practical value for innovative construction technologies.

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INTRODUCTION

Concrete is a common fundamental material in construction industries due to its readily available and fairly less expensive nature (Abdulla, 2017). However, concrete has some drawbacks, such as low tension resistance and ductility, causing failure by cracking under tension with limited deformation (Abdulla, 2021). Some confinement techniques have been developed to overcome these defects (Abdulla, 2021b, 2022a, 2022b). One such prominent method is the concrete-filled steel tubes (CFST), in which concrete is encased within a steel tube, therefore providing continuous confining pressure and hence improving stiffness, strength, and overall structural stability. Fig. 1 indicates different type of composite column used in application.

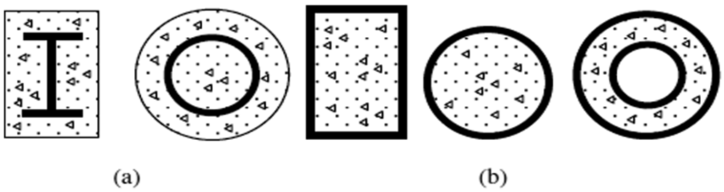

Figure 1. Composite columns with various types (a) Encased and (b) concrete-filled. (Abbas, 2023)

While CFSTs are effective, steel tubes present certain drawbacks, including vulnerability to corrosion in harsh environmental conditions and elevated material and labor costs. These limitations have driven the search for alternative materials. Polyvinyl Chloride (PVC) tubes offer a promising solution, as they are corrosion-resistant, cost-effective, lightweight, and durable, making them well-suited for use in confined concrete applications. Fig. 2 shows a PVC-confined concrete specimen prepared and tested by Fakharifar and Chen (2017).

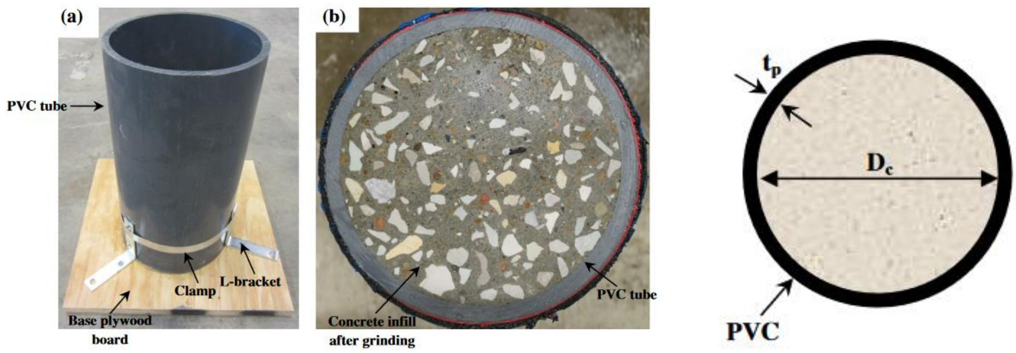

Figure 2. Specimen preparation (a) PVC tube before casting; (b) ground end. (Fakharifar and Chen, 2017)

PVC offers several advantages over traditional steel in confined concrete applications. PVC is substantially less expensive than steel and fiber-reinforced polymer (FRP) composites, with a cost ratio of approximately 0.5 compared to steel (Abdulla, 2021a; Abdulla, 2022a) Additionally, PVC tubes expedite construction times by serving as stay-in-place formwork, further reducing labor costs (Abbas, 2023; Abdulla, 2023). PVC exhibits impressive durability, specifically in harsh environments, due to its high corrosion resistance, chemicals, and weathering (Alinejad, 2021; Alves, 2009). Studies indicate that PVC pipes, even after 60 years in soil, show no signs of deterioration and could potentially last another 50 years, making them highly sustainable for construction (Bazli, 2016). PVC’s low density makes it easy to handle and transport, facilitating faster and simpler construction (Gupta 2013, Isleem et al, 2022). Additionally, PVC's low thermal conductivity (only 0.45-0.6% of steel) creates stable curing conditions for the concrete core, which can improve the strength and durability of confined concrete structures (Alinejad et al., 2021; Bazli et al., 2016; Feng et al., 2020). Research also indicates that PVC confinement enhances the strength, ductility, and energy absorption capacity of concrete columns, contributing to better structural performance (Bazli et al, 2020; Mammen and Anthony, 2017; Masajedian, 2011).

Various parameters significantly influence the performance of PCC columns. The diameter, thickness, and height of PVC tubes affect the load-carrying capacity, confinement effectiveness, and failure modes of PCC columns (Abdulla, 2017, 2021a, 2021b, 2022). Increasing the PVC tube thickness improves confinement and column strength, while larger diameter columns, although having higher load-carrying capacity, often show lower compressive strength due to stress distribution over a larger area (Abdulla, 2023, Bazli et al. 2020). Yield and tensile strength of PVC tubes are crucial for effective confinement. Higher strength PVC tubes delay concrete cracking and contribute to enhanced axial compressive strength (Isleem et al., 2022; Kumutha and Vijai, 2016; Lu et al., 2015). Lower strength concrete is more ductile and benefits significantly from PVC confinement, whereas higher-strength, more brittle concrete may fail before fully utilizing the confining action of the PVC tube. Incorporating supplementary cementitious materials, like rice husk ash (RHA), has been shown to improve concrete strength (Bazli et al, 2020; Askari et al., 2020; Morozov et al. (2014). Other parameters include fiber reinforcement in the concrete mix, which enhances strength and ductility, and the addition of a foam layer between PVC and FRP wrap in hybrid systems, which improves ductility and mitigates brittle failure (Ozbakkaloglu and Lim, 2013; Raheemah and Resan, 2019; 2020).

Current empirical models for predicting concrete strength have several significant limitations. Traditional empirical formulas typically rely on linear or simplistic mathematical relationships that fail to capture the complex, nonlinear interactions between structural parameters. These models often oversimplify the intricate relationships between PVC tube thickness, column diameter, and concrete compressive strength. Existing empirical models are usually developed based on a narrow range of experimental data, restricting their applicability to specific geometric configurations and material properties. This narrow scope significantly reduces their generalizability across diverse structural designs. Conventional models struggle to account for emerging materials and novel confinement techniques. They are largely static, unable to incorporate new insights or technological advancements in material science and structural engineering. Most empirical models require manual calculation and lack the predictive flexibility of modern machine learning approaches. They cannot efficiently process multiple variables or quickly adapt to changing design parameters. Existing models often inadequately represent the complex interactions between PVC tubes and concrete cores, particularly regarding confinement effects, stress distribution, and material behavior under varying loading conditions.

The novelty of this research lies in its innovative application of machine learning techniques to predict the compressive strength of PVC-confined concrete, addressing critical limitations in traditional structural engineering methodologies. By leveraging Artificial Neural Networks (ANN) and Support Vector Machines (SVM) with a comprehensive Finite Element Analysis (FEA) dataset, the study introduces a sophisticated, data-driven predictive framework that surpasses conventional empirical models. This approach demonstrates unprecedented capability in capturing complex material interactions, offering superior predictive accuracy across varied column geometries and material configurations. Moreover, the research pioneers a methodological innovation by employing advanced cross-validation techniques and comparing multiple ML model architectures, thereby providing a flexible and adaptable tool for structural performance assessment. The work not only showcases ML's transformative potential in structural engineering but also supports broader sustainability goals by facilitating rapid, accurate strength prediction of alternative construction materials like PVC-confined concrete, potentially reducing resource-intensive experimental research and accelerating innovative material adoption in the construction industry.

This study applies machine learning techniques to predict of the axial compressive strength of PVC-confined concrete (PCC) short columns. The objectives are be

- The ANN-and-SVM-based ML model development on a large-sized database generated by FEA.
- Comparing their models' performances to one proposed by Abdulla 2021c.
- Identification of the key parameters that affect axial strength in PCC columns.
- Contributing to more robust predictive tools that enhance PVC's use in construction.

By addressing these objectives, this research seeks to create accurate, reliable, and adaptable predictive models, promoting the adoption of PVC-confined concrete as a sustainable, cost-effective material in construction.

MATERIALS AND METHODS

Description of Database

The data used in this study was gathered from a M.Sc. Thesis (Topal, 2022) where Finite Element Method (FEM) analysis was conducted using ATENA 3D (Cervenka, 2021), a nonlinear finite element analysis software. In reference (Topal, 2022), PVC composite columns filled with concrete are modelled and their behavior simulated by the ATENA 3D software. The model is discretized by a finite element mesh, whose global element size is equal to 0.03 m, as found optimum from comparative analyses carried out with different mesh sizes. The base was constrained by providing supports, and axial loads were applied in the Z direction on the top surfaces. This type of boundary condition provided that the displacement could occur without restriction in the X and Y directions but was constrained at the base in the Z direction. A set of predefined deformations was imposed in steps of 5 mm per increment in the Z direction to mimic the effects of compression. Material properties of both PVC and concrete were carefully created using the interface for material definition in the software, based on empirical data. Figure 3 presents a finite element model elaborated in a framework of ATENA software.

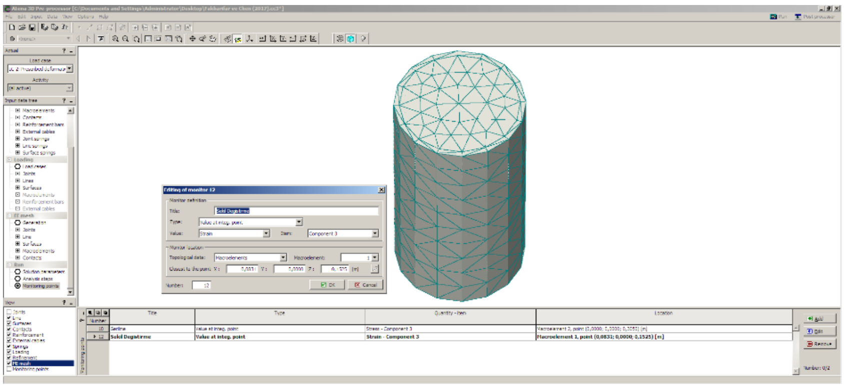

Figure 3. FEM model created by (Topal, 2022)

A total of 200 models were created by varying the following parameters: PVC thickness (ranged from 3 mm to 7 mm), concrete core diameter (Between 100 mm and 160 mm), column height (From 150 mm to 300 mm), concrete compressive strength (45 MPa and 60 MPa).

The model was calibrated with the help of experimental data borrowed from literature, a study by Fakharifar and Chen (2016). Calibration ensured that the FEM model results were close to real experimental observation as shown in Fig. 4.

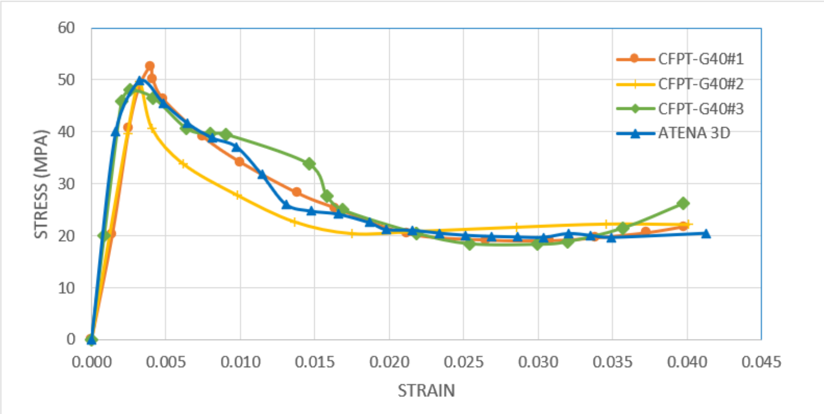

Figure 4. Comparison of reference models and FEM model (Topal, 2022)

The obtained results of the FEM model were then compared and validated against experimental data. It could be revealed in the analysis that the result showed good agreement with experimental data, especially on the behavior of the load-displacement and failure modes. The influence of the mesh size was studied, showing that the smaller-sized elements provided more accurate results, choosing 0.03 m as optimal. This resulted in the correct model for axial compressive strength and the developed behavior by PVC-confined concrete columns under different conditions. The dataset consists of the following variables:

FEM Models: Represents the model identifier.

H: Height of the concrete-filled PVC composite columns (in mm).

D: Diameter of the core concrete (in mm).

t_p: Thickness of the PVC tube (in mm).

D/t_p: The ratio of diameter to PVC thickness.

H/D: The height-to-diameter ratio.

f_c: 28-day compressive strength of the core concrete (in MPa).

f_{cc}: Compressive strength of the composite sample (in MPa).

Table 1 provides a statistical summary of key variables related to concrete-filled PVC tubes, focusing on parameters such as height (H), diameter (D), thickness of the PVC tube (t_p), and compressive strength (f_c and f_{cc}). Table 1 shows that the experiments cover a broad range of concrete column geometries and material properties, and the confinement provided by the PVC tubes leads to increased compressive strength in the tested specimens.

Table 1. Statistical summary of data

	H	D	tp	D/tp	H/D	fc	fcc
count	200	200	200	200	200	200	200
mean	225	130	5	28.4144	1.7785	52.5	56.63785
std	56.04	21.27	1.42	10.08	0.54	7.52	8.17
min	150	100	3	14.29	0.94	45	43.12
25%	187.5	115	4	20.71	1.36	45	48.675
50%	225	130	5	26	1.73	52.5	57.39
75%	262.5	145	6	33.33	2.095	60	63.2725
max	300	160	7	53.33	3	60	78.2

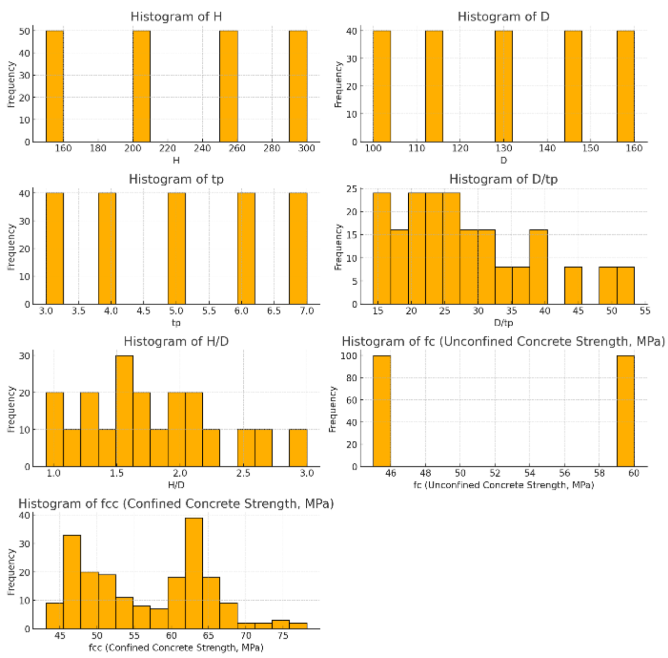

Figure 5. Distribution of Parameters

Fig. 5 reveals several key distribution patterns across the parameters. *H* and *D* display a fairly uniform distribution, suggesting an even spread of heights and diameters across the FEM models. Similarly, t_p shows a relatively even distribution throughout the dataset. However, the D/t_p ratio exhibits a skewed distribution, with a higher concentration of models in the lower ranges (15-30). The *H/D* ratio presents a varied distribution, with more models falling in the middle range (1.5-2.0). f_c is notably concentrated at specific values, particularly 45 and 60 MPa, indicating that the models used these unconfined strengths. Lastly, f_{cc} shows a broader distribution with a slight skew toward lower values around 50-60 MPa.

Modeling Strategies and Method

Support Vector Machines

The support vector machine (SVM) was originally introduced by Boser et al. as an artificial intelligence technique for solving classification problems (Boser, 1992). Over time, researchers have extended the application of SVM to handle regression tasks, coining this approach Support Vector Regression (SVR). With a solid mathematical foundation rooted in statistical learning theory, SVMs have shown outstanding performance across various applications, including face recognition, text analysis, bioinformatics, and image processing. These successes highlight SVMs as one of the most advanced techniques in data mining and machine learning, alongside other computational methods like fuzzy systems and neural networks (Wang, 2005). The core principle of SVM is identifying the optimal linear separator, which can differentiate two classes while allowing for minor discrepancies within a defined margin of error. This approach seeks to determine the best hyperplane that separates the datasets. In the case of support vector regression (SVR), the goal is to find a function that approximates the true output values with a maximum deviation of ε and to position two hyperplanes parallel to this function, aiming to minimize the distance between them (Chen et al., 2004).

Although many kernel functions are used in machine learning, this study employs four distinct ones. These functions are:

Linear function: $K(x_i, x) = x_i x$ (1)

Polynomial function: $K(x_i, x) = (x_i(x+1))^d$ (2)

Radial-based function: $K(x_i, x) = \exp\left[-\dfrac{(x_i - x)(x_i - x)}{2\sigma^2}\right]$ (3)

Sigmoid function: $K(x_i, x) = \tanh(x_i(x+1))$ (4)

where x_i and x, are the training and test inputs, respectively, σ is the global function and d is the size of the input vector.

SVM has been applied in various areas, including modeling concrete strength, corrosion, structural safety, and properties of self-compacting concrete, among other fields. In a review, Çevik et al. (2015) summarized the applications of support vector machines in structural engineering.

Artificial Neural Networks

Artificial neural networks (ANNs) are computational models designed to simulate the functioning of biological neural networks in the human brain. ANNs are composed of interconnected layers of nodes, or neurons, which process and learn from data by identifying patterns (Goodfellow, 2016). These models are widely used in machine learning and artificial intelligence, especially for tasks such as pattern recognition, classification, and prediction (LeCun et al., 2015). Neurons are the basic units for processing information in an ANN. Each neuron takes one or more inputs, performs a mathematical operation, typically a summation of weighted inputs followed by passing the output through an activation function, and produces an output (Haykin, 2009). ANNs have neurons organised into layers: *Input layer:* The input data is fed into this layer in its raw form. Examples might be height, diameter and compressive strength for engineering datasets. *Hidden layers:* These intermediate layers perform computations on the inputs, allowing the network to capture complex, non-linear relationships. The more hidden layers an ANN has, the better it is at capturing complex data patterns (Goodfellow, 2016). *Output layer:* This layer represents the prediction of the model. Outputs may include predicted compressive strength for structural applications. *Weights and biases:* Each neural network connection is assigned a weight that represents the strength of the input in making predictions. Biases allow the activation function to be shifted to better approximate non-linear relationships in the model (Bishop, 2006). *Activation functions:* These help to introduce non-linearity into the model so that it can learn complex patterns. The three most commonly used activation functions are rectified linear unit, sigmoid and hyperbolic tangent (LeCun, 2015). *Training:* In the training process, the ANN modifies the weights and biases to achieve a minimum difference between the predicted and actual output. These modifications are made using various optimisation algorithms such as gradient descent, and the process is called backpropagation (Rumelhart et al., 1986). The process of backpropagation updates the weights of the model by propagating errors from the output layer to the hidden layers in such a way that the network improves after each step.

In short, ANNs are a tool for solving complex problems that may involve some sort of pattern identification and prediction, and their applications, such as in structural engineering for predicting materials and behaviour based on some input features. Various areas where ANNs are used include image recognition, natural language processing, financial forecasting and, for this area of research, predicting the axial behaviour of PVC-confined concrete columns.

Hyperparameter optimization for the machine learning models was conducted using grid search. For the ANN model, the hyperparameters tuned included the number of hidden layers (1–3), the number of neurons per layer (10–100, in increments of 10), the learning rate (0.001–0.1), and the activation functions (ReLU, sigmoid). For the SVM models, the kernel type (linear, polynomial, RBF, sigmoid), the regularization parameter C (0.1–100), and the kernel-specific parameters such as the degree for polynomial kernels and γ for RBF kernels were explored.

A 10-fold cross-validation approach was employed to assess the robustness of the machine learning models. The dataset was randomly split into five subsets of approximately equal size. For each fold, four subsets were used for training, and the remaining one for testing. The process was repeated five times, ensuring that each subset served as the test set once. The mean, R^2 and RMSE across all folds were computed to evaluate the model performance.

ML Modeling

Scikit-learn, a Python library, was used for modelling with SVM and ANN. Python libraries such as Pandas and Numpy were also used for the data preprocessing mentioned in the data preprocessing section. Before modelling, the database was divided into two parts as 20% test data and 80% training data.

A strength model based on empirical data proposed by Abdulla 2021c was used to validate the accuracy of the ML models. Both the statistical results (R^2 and RMSE) and the scatter plot were compared with the strength model. Main formula proposed by Abdulla 2021 is

$$f_{cc} = \left(4.6 - \left(\frac{H}{t}\right)^{1.01}\left(\frac{t}{D}\right)^{1.247}\right) + 4.95\left(\frac{f_l}{f_{co}}\right)^{3.4} f_{co}^{0.1} + 0.94 f_{co} + 0.5 f_u \xi \tag{5}$$

where H denotes the column height, while t represents the thickness of the PVC tube, and D stands for the diameter of the PVC tube. The term fco refers to the unconfined concrete compressive strength, an essential factor in determining the column's base strength. Additionally, fl is the lateral confining pressure exerted by the PVC tube, contributing to the overall confinement effect. The ultimate tensile strength of the PVC tube, labeled as fu, impacts the column's ability to withstand axial loads, and the confinement index, represented by ξ, quantifies the degree of confinement applied to the concrete core.

$$\xi = \frac{f_y \cdot A_p}{f_{co} \cdot A_c} \tag{6}$$

$$f_l = \frac{2 \cdot t \cdot f_y}{D - 2t} \tag{7}$$

RESULTS AND DISCUSSION

Figure 6 presents actual vs. predicted scatter plots for 10 different models predicting the confined concrete strength (f_{cc}). These plots include a diagonal line representing ideal predictions, where predicted values match actual values. Each models' performance is evaluated based on R^2 (coefficient of determination) and RMSE (Root Mean Squared Error) values, which provide insight into model accuracy and error in both training and testing data.

The Artificial Neural Network (ANN) model shows exceptional performance, with an R^2 of 0.99 for both training and testing data, indicating near-perfect alignment with the actual values. The RMSE values (0.81 for training and 0.83 for testing) are among the lowest across all models, implying minimal prediction error and strong generalization. This suggests that ANN captures the relationship between features and f_{cc} very effectively, producing predictions closely clustered around the ideal diagonal.

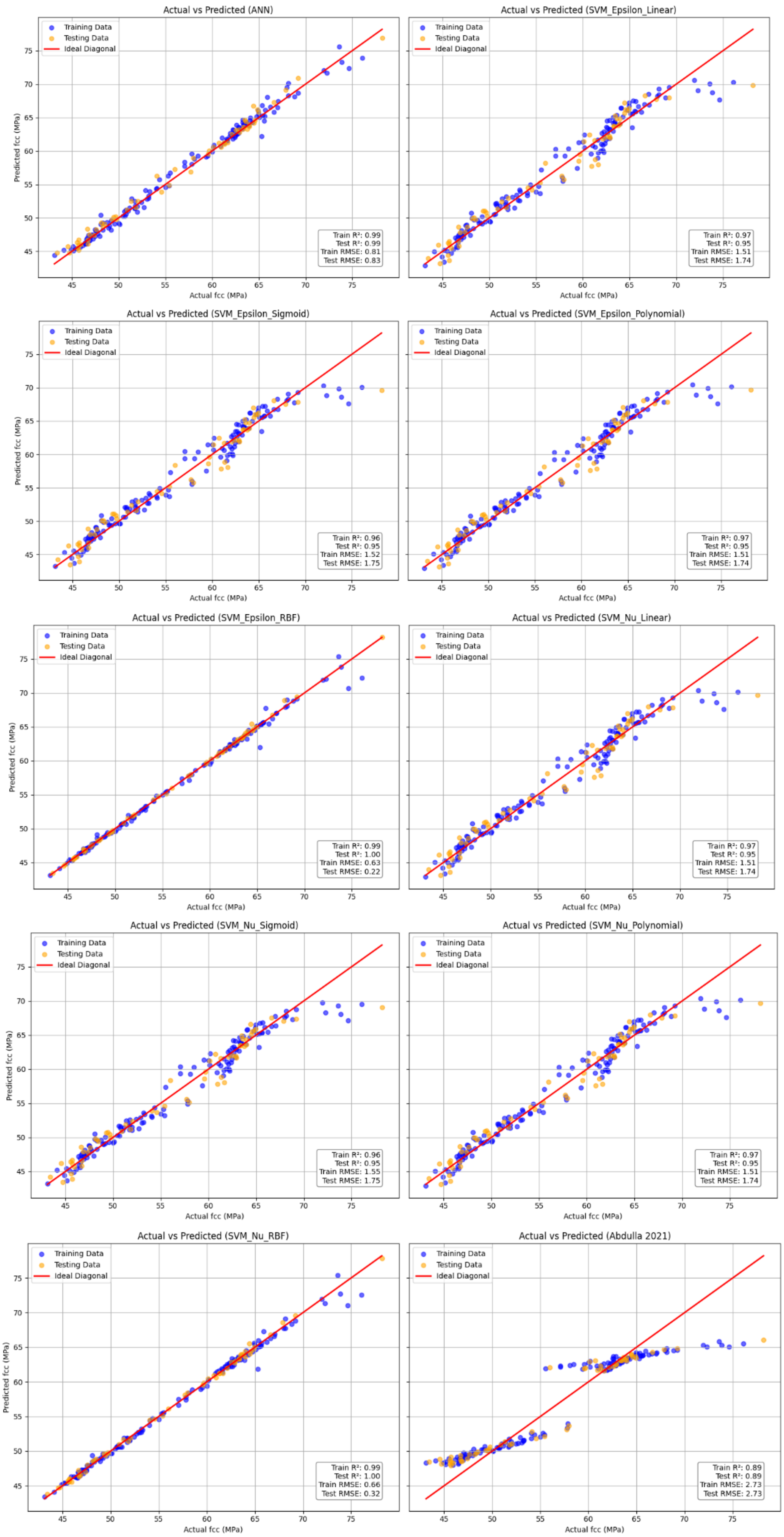

Figure 6. Actual vs. predicted scatter plots

SVM Epsilon Linear model performs slightly worse than that obtained by ANN. The R^2 values amount to 0.97 and 0.95 for training and testing, respectively. The RMSE values are 1.51 for the training set and 1.74 for the test set-higher than in the case of ANN-with high prediction error on the test set. This model generally fits well; however, its deviations from the ideal line indicate limited performance in capturing nonlinear relationships.

On the other hand, SVM Epsilon Sigmoid and Polynomial perform very similarly to each other, for the training R^2 values of 0.96 and 0.97 respectively, while for testing are identical, 0.95. Their RMSE for the training/testing is around 1.5–1.75 for both higher than the ANN model, but comparable to the linear kernel. These kernel-based models seem to fit these data quite well, but there is a systematic deviation from the ideal line, at least for higher values of f_{cc}, which hints that polynomial and sigmoid kernels are not flexible enough to capture the complexity of the relationship.

The performance of the SVM Epsilon RBF is very good with R^2 values of 0.99 for training and 1.00 for testing, implying that the model achieved the best fit to the data. The RMSE values are particularly low, hence giving an excellent result in both accuracy and generalization: 0.63 for the training set and 0.22 for the test. This is also one of the best models, along with ANN, since the predictions are very tightly clustered around the ideal line. Because of the flexibility in the RBF kernel, the nonlinear relationships could be well captured, and, hence, very high predictive performance.

The performances of the Nu Linear and Nu Polynomial models of SVM are about the same, where the above models give R^2 values around 0.97 for training and 0.95 for testing. Also, for such models, the RMSE was relatively similar, in the range of 1.5–1.75 for both datasets, indicating a reasonable prediction error. These models follow the overall trend but deviate from the ideal diagonal at higher values of f_{cc}, suggesting that there is a limitation in dealing with complex and nonlinear relationships.

This is emphasized in the SVM Nu RBF model, which had excellent R^2 values of 0.99 for the training set and 1.00 for the test set, coupled with very low RMSE values of 0.66 and 0.32 for the training and test sets, respectively. This is not far from the performance of the SVM Epsilon RBF model, which further strengthens the RBF kernel when there are complex nonlinear patterns to deal with. The near-perfect alignment of actual and predicted values demonstrates this model's high accuracy and reliability.

Meanwhile, the Abdulla 2021c model from the reference has inferior performance as compared to ANN and SVM models discussed. It has a moderate R^2 fit with actual values at 0.89 for the training and testing datasets. The RMSE of the Abdulla 2021 model is, however, the highest of all discussed, with a value of 2.73 for the training and testing datasets. The scatter plot of residuals shows that the larger the value of f_{cc}, the more deviated the residuals are from the ideal line, hence this could be a too rigid model to capture the full range of variation in the data.

Table 2. Statistical metrics

Metric	ANN	SVM-RBF	SVM-Linear	Abdulla 2021c Model
R^2 (Training)	0.99	0.99	0.97	0.89
R^2 (Testing)	0.99	1.00	0.95	0.89
RMSE (Training)	0.81	0.63	1.51	2.73
RMSE (Testing)	0.83	0.22	1.74	2.73
MAE (Training)	0.50	0.42	1.20	2.00
MAE (Testing)	0.55	0.18	1.30	2.10
MAPE (%)	1.23	0.97	3.10	5.50

In addition to R^2 and *RMSE*, Mean Absolute Error (*MAE*), Mean Squared Error (*MSE*), and Mean Absolute Percentage Error (*MAPE*) were calculated to provide a holistic evaluation of model performance. The Adjusted R^2 was also computed to account for the number of predictors, ensuring a fair comparison across models with different complexities. Table 2 compares the statistical metrics of models.

Briefly, the highest performance was done for ANN and SVM-RBF Epsilon and Nu models, by yielding almost perfect R^2 values and very low RMSE, hence high predictive power and accuracy. Indeed, the above-mentioned models are of high capacity to capture complex relationships in data, as evidenced by their close adherence to the ideal diagonal line. Among the rest, the models SVM Linear, Sigmoid, and Polynomial perform reasonably well but reflect higher error rates and therefore are limited in capturing non-linear patterns. Finally, the Abdulla 2021 model presents the lowest performance, with higher error rates and lower R^2, reflecting its limitations in comparison with modern machine learning techniques. The ANN and SVM-RBF models outperformed other models across all metrics, achieving lower RMSE, MAE, and MAPE values. The SVM-RBF model showed particularly strong generalization capability, as evidenced by its minimal RMSE and MAE in the test set. In contrast, the Abdulla 2021c model exhibited higher error rates across all metrics, underscoring its limitations in capturing complex nonlinear relationships. Moreover, this analysis underlines the better performances achieved by ANN and SVM RBF in forecasting confined concrete strength and therefore positions these models as the most reliable for practical applications in the area.

One limitation of this study is the relatively small dataset size (200 samples), which may affect the robustness and generalizability of the machine learning models. While the models demonstrated high predictive accuracy based on the available data, larger datasets are typically preferable in machine learning applications to better capture the variability in the data and avoid potential overfitting. The limited dataset size might restrict the ability of the models to generalize to unseen scenarios or account for outliers effectively.

To mitigate the potential limitations posed by the dataset size, techniques such as cross-validation and model regularization were employed to ensure robust model evaluation and reduce the likelihood of overfitting. Moreover, the dataset was generated from a reliable source, using a calibrated finite element analysis (FEA) model validated with experimental data, which increases confidence in the dataset quality despite its size.

CONCLUSION

This paper presents a study on the feasibility of PVC as an economical and durable confinement material for concrete with focus on enhancing axial compressive strength of short concrete columns. This research study illustrates how predictive modeling can capture the complex relationship among the structural parameters and compressive strength by employing FEA and using ML models like ANN and SVM. In fact, a high R^2 coupled with a low RMSE obtained for ANN and SVM using an RBF kernel underscores that both models have a high predictive accuracy and robustness to estimate the compressive strength of PVC-confined concrete columns.

The presented ML-based approach holds substantial advantages over traditional empirical models in terms of being able to be inclusive for nonlinear interactions among parameters pertaining to PVC thickness, column diameter, and concrete strength. As a result, ML models should be quite well-suited for substantially varied conditions and maybe even for new geometries of columns and material combinations that may not be handled by their empirical counterparts.

There are a few limitations identified despite the promising results arising from this study. Though this study uses the data through FEA, which is calibrated with previous experimental studies, these ML models have not been fully verified through real-world testing to establish their generalizability. Moreover, while high predictive performance of the ML models could be realized using current methodologies, interpretability of said models remains limited, especially to practical engineering applications. Other future studies may delve into more real-world experimental data as a means of validation and refinement of the ML predictions. Moreover, this analysis, when extended to other factors of environmental durability such as UV exposure and chemical resistance of PVC, would give a better understanding of the performance of PVC in structural applications.

In short, this research shows that PVC represents an effective greener confinement material and highlights the value of ML techniques toward improving predictive accuracy for structural performance. The results contribute to the accumulating literature on civil engineering by providing a way to create adaptive, data-driven predictive tools that support increased diffusion of the PVC-confined concrete in the construction industry. Future research could focus on incorporating real-world experimental data to validate and refine the ML predictions further. Expanding the analysis to consider environmental durability factors, such as UV exposure and chemical resistance of PVC, would also provide a more comprehensive understanding of its long-term performance in structural applications.

Conflict of Interest

The article authors declare that there is no conflict of interest between them.

Author's Contributions

The authors declare that they have contributed equally to the article.

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