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Scientific paper
ISSN 0351-9465, E-ISSN 2466-2585
https://doi.org/10.62638/ZasMat1437

Zastita Materijala 67 ()
(2026)

Analysis of concrete properties through machine learning models

ABSTRACT

Machine Learning (ML) models, the most prominent methodologies, are now being employed in practically all fields to address difficult and complex problems with a coding-free solution. ML has recently been used in enormous civil engineering applications including cost analysis during construction phase, workforce management in construction site, monitoring the structural health and building life cycle, construction waste management, analysing the mechanical properties (compressive, axial strength, etc.), shear strength and incorporation of various fibers/polymers/demolition wastes in the concrete. This review paper investigates the applications of ML models particularly XGBoost, ANN, RF and SVM used to predict the values of concrete properties (compressive and shear strength) most precisely. The interpretation of input variables across different models is diminished due to constrained datasets. The emplacement of ML models in workplaces is challenging due to the scarcity of datasets pertaining to structures in natural environments. The knowledge gaps and recommendations to enhance the research were also reviewed in this work.

Keywords: *Machine learning, concrete properties, mechanical properties, shear strength.*

1. INTRODUCTION

Concrete is the man-made substance that is most often used after water, approximately utilized 30 billion tonnes globally. Cement is the vital ingredient in concrete, its annual production crossed around 3.3–4.2 billion tonnes throughout the land. The amount produced is doubled from the preceding decade and it emits 7-8 % of CO_2 as of now [1]. The cement gets harder and binds the aggregates when the water is poured and forms concrete. Concrete urbanizes and beautifies the world today, but it will become a challenge tomorrow due to the carbon footprints and extinction of non-renewable aggregates [2].

The researchers, industrial innovations, and the governments are in urgent need to reduce the environmental footprint. It is promoted through the adoption of substitute materials (e.g., industrial by-products, recycled materials, and other natural waste resources), advanced technologies (self-healing concrete, 3D printing, etc.,) and carbon management systems during cement production [3]. On the other hand, the concrete research is widely focusing on sustainability, enhancing performance and smart concreting [4,5].

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Paper received: 02. 05, 2025.
Paper corrected: 29.12.2025.
Paper accepted: 29.03.2026.

The replacing materials for concrete's components are identified through their estimated material properties, which should match with conventional ones and improve the performance and strength. The material's mechanical and durability properties are estimated via various laboratory test methods, it becomes challenging, loss of resources, time consuming and too complex to solve without expert knowledge. These difficulties are rectified through the artificial intelligence (AI) using machine learning (ML), which aims to replicate the gist of human cognition at the extreme level [6,7].

1.1. Overview of Artificial Intelligence (AI)

In 1956, Dartmouth College workshop established the term "AI" [8]. Artificial Intelligence is a computational practice that uses symbol manipulation techniques and symbolically structured knowledge to tackle complex technical issues in traditional approaches. In order to provide additional context for the state of the art, it is essential to define some of the terms, one such term is machine intelligence (MI), which is frequently used interchangeably with AI.

MI deals with various intelligent problems includes clustering, computer vision, classifications, etc., but is generally used to refer the machine's intelligent behaviour and reasoning ability like humans. However, AI called as machine's capacity to replicate human cognitive functions in an intelligent manner. Another key word is cognitive computing (CC), that is modelled after the human mind's potential [9,10]. Cognitive systems have the ability to resolve issues by simulating human thought processes and reasoning. These kinds of systems rely on machines' capacities for measurement, reasoning, and experience-based adaptation [11,12].

The capacity to analyse large number of datasets, realtime training and adaptive learning and probabilistic identification of pertinent patterns are the primary traits of CC systems. In technical terms, AI refers to the computers and other technologies that possess intelligence, whereas CC focuses on problem-solving techniques that mimic human thought processes. When it comes to dealing with people, the biggest distinction between AI and CC may be identified. Every AI model has a factor that confirms what has to be done. In contrast, CC systems behave, think, and learn just like people.

1.2. Applications of AI

AI has been developed the innovation ideas in several fields, including information theory, cybernetics, linguistics, and neurophysiology, Philosophy, imagination, fiction, computer science, robots with human-like intellect, electronics, and engineering inventions and so on [13]. Alan Turing [14], who proposed the intelligence test that marked a paradigm shift in the sphere of AI because it goes over the accepted theological views and mathematical conclusions in machines' intelligent. Sixty years later, big data and computer processing power are rapidly updated to exceed humans in a wide range of fields, including learning [15,16].

1.3. AI in construction

Advancement in science and technology has propelled AI and ML in almost all the fields. The major subfields of AI include ML, Neural Networks (like brain network) and Natural Language Processing (NLP), computer vision, automated planning and scheduling, optimization, knowledge-based systems and robotics. AI can perform advanced tasks like problem solving, decision making, image and sound recognition, understanding natural languages, learning through data, reasoning ability, adoption of new technologies or information, etc. Especially, ML is the subdivision of artificial intelligence which works through the set of data [17].

Since 1960s, when AI was in beginning stage, optimization technology in construction industry has long been a subject of great research interest. According to recent research trends, ML has become the more popular in almost all subfields of construction industry than knowledge-based systems. It can able to address the problems in skilled labour shortages, 3D printing, UAV technologies and exoskeletons for construction work progress and brought robotics within this.

The intrusion of AI in construction sector, over 60 % of that research has been done in the past ten years. Innovative technologies like block chain, the Internet of Things (IoT), quantum computing and cybersecurity have all benefited from this research. Instead of merely enabling human-to-human communication, the internet has developed to allow the communication between other objects and humans establish a smart environment [18]. Recent advancements in sensors, cloud computing, actuators and wireless technologies are more affordable and faster devices with more processing power have all contributed to this transition. The construction industry has adopted IoT and AI in a number of ways such as energy conservation on demand for intelligent building energy monitoring [19,20].

The influence of AI in structural engineering as an emerging technology especially, ML, DL and pattern recognition (PR) have established as new intelligent models. The AI models are developed and used in structural health monitoring, earthquake engineering, damage detention, etc. ML models reduce the complications while predicting the properties of fresh and exciting concrete using conventional methods. The ML model performance mainly depends on the data collected, which can be satisfied by the sensors that capture more data than traditional methods. The sensors are durable and affordable, which can lower the inspection and field experiment cost. The authors also discussed the issues arise on efficiency and robustness of the sensors data [21].

The concrete technology has been developed through AI and an increase in awareness of carbon footprint alleviations. The substitute materials such as industrial waste, natural waste, etc., are evolved and achieve a strength almost equal to or greater than the conventional resources. This strength is calculated by estimating the compression strength, shear strength, flexural strength, tensile strength, modulus of elasticity and rigidity of chosen material, etc., and the process is made more efficient through ML models. This analysis explores the recent research trends and future focus of compressive and shear strength of different concrete type or structure; these parameters are pertinent to select the suitable materials to replace the conventional one in concrete.

2. COMPUTATION OF PROPERTIES OF CONCRETE WITH ML MODELS

2.1. Compressive Strength (C-S)

Yang Yu et.al (2018) established a novel predictive model, Support Vector Machine (SVM) to predict the C-S of high-performance concrete (HPC). The authors proposed a model for the input variables (water content (W), fine aggregate (FA), coarse aggregate (CA), blast furnace slag, flyash and super plasticizer (SP), curing age, etc.) and to get the C-S as output. The models were improved by using enhanced cat swarm optimization (ECSO) to increase its performance. The authors concluded that the SVM model was most effective for the statistical classification and PR. The optimized model showed their improvement in the convergence rate and regression accuracy [22].

Qinghua Han et. al (2019) proposed Random Forest (RF) model and optimization techniques to enhance the performance and simplifying the determination of input parameters (cement (C), W, flyash, blast furnace slag, SP, CA, FA and age) and the response parameter C-S of HPC. In this study, the authors analysed two different variations in parameters without eliminating fundamental parameters as group A set and group B set in initial stage. It showed identical results because this model was insensitive to the input parameters. In the second stage, the authors enhanced the model performance by optimizing the input variables. The model results were improved, which maximized the coefficient of determination (R^2) value from sixth to third position, minimized mean absolute percentage error (MAPE) value from third to second place and minimized mean absolute error (MAE) and root mean square error (RMSE) from second best to the best model. According to the researchers, the model developed by the suggested method indicated the greater generalization capacity than the model developed without optimizing input variables [23].

De-Cheng Feng et. al (2020) employed adaptive boosting (AdaBoost) models for prediction, validation and comparison of C-S of concrete. The ML model predicted the concrete’s C-S by integrating weak learners has low error and generate strong learner with the input parameters as ordinary Portland cement (OPC), CA, FA, W, SP, blast furnace slag, flyash and curing age. The model validation attained the average accuracy of 95% in determination coefficient using 10-fold cross validation process and compared with standalone models, Artificial Neural Network (ANN) and SVM which showed the advantages over it. The authors declared that the proposed model was a baseline model which can predict C-S depends on C, W and curing time of concrete at different time with different mix proportion and it may be enhanced with multi-output model [24].

Ayaz Ahmad et.al (2022) estimated the C-S of fly-ash based geopolymer concrete by using three supervised ML algorithms namely decision tree (DT), Adaboost regressor, bagging regressor (BR). ML models developed for nine input parameters (flyash, FA, CA, Na2SiO3, NaOH, SiO2, NaOH Morality, Na2O and age) and output parameter as C-S. The model performance can be evaluated and confirmed by the R^2, MAE, RMSE, mean square error (MSE) and using k-fold cross validation technique. The BR model has R^2 - 0.97 and lesser other error values confirms which is best than other two models [25].

Mohammad Mohtasham Moein et. al (2023) analysed the concrete’s mechanical properties using ML, DL and ANN. ML provide several advantages over statistical and experimental statics including best possible accuracy, high performance, ability to adapt to complex situations and lowest possible cost. The authors used four factors namely, the R^2, MAE, MAPE and RMSE to compare the accuracy of ML/DL models with statistical methods. The authors also discussed the efficiency of ML/DL models including SVM and ANN models, which can operate with less error and evolutionary algorithms and decision tree model can be performed good enough to explicitly calculate the correlation of input and output parameters. Ensemble model has provided high accuracy but it consumes more computation time and becomes complexity. [26]

M.Z. Naser (2023) investigated and compared the performance of five coding-free and automated ML models like BigML, Dataiku, DataRobot, Exploratory and RapidMiner on fields related to civil engineering. In this research, the adopted datasets were detailed, and the benchmarking and comparison of feature importance using the algorithms listed above was done for various applications. The researcher assessed and compared the regression metrics R^2, MAE and RMSE, and the classification metrics accuracy, log loss error and area under the receiver operating characteristic (ROC) curve (AUC) for the algorithms in different conditions. The Extreme Gradient Boosting (XGBoost) algorithm was utilized to examine the compressive strength of ultra-high-performance concrete (UHPC), light gradient boosting machine (LGBM) algorithm was applied to determine the axial strength of concrete filled steel tubular columns, gradient boosted tree algorithm was used to predict the emission of CO_2 in vehicles, default neural networks was explored to classify the fire induced concrete mixtures, decision tree was used to identify the chemical composition of potable water and random forest algorithm was applied to classify the bridge failures. The author discovered that the coding free algorithm was similar to the coding-based algorithm when all algorithms are used in their default settings and also concluded that the tuning of the platform’s model increase the coding free models would be more effective. [27]

Table 1. Summary of recent ML based studies on compressive strength prediction - highlighting commonly used algorithms, relative performance and key insights across conventional and new concrete types

Authors (Year)	Concrete Type	Data set Size	Input parameters	ML Models Used	Best Model	Key insight
Elshaarawy et al. (2024) [28]	Flyash concrete	1030	C, W, FA, CA, blast-furnace-slag, fly ash, SP, curing days. (8)	Non-ensemble models, Ensemble models	CatBoost (Ensemble model) (R^2 - 0.966, RMSE - 3.06, MAE - 2.27)	Most influential input variables: Age and cement content Does not account for temperature and humidity during curing Precise predictions in varying compressive strength ranges; potential lack of generalizability to different datasets and conditions
Sah & Hong (2024) [29]	Normal concrete	1030	C, W, FA, CA, SP, blast furnace slag, fly ash and age. (8)	ANN, SVM, RT, MLR	ANN in accuracy and efficiency.	Most influential input variables: W, C, CA, FA, SP, blast furnace slag and fly ash and age Unique challenges: Highly nonlinear relation between C-S and its constituents.
Paudel et al. (2023) [30]	Flyash concrete	633	C, W, FA, CA, % of SP, fly ash, curing days (7)	MLR, SVR, AdaBoost Regressor, BR, RF Regression, XGBoost Regressor,	XGBoost Regressor (R^2 - 0.95, RMSE - 3.06, MAE - 2.13)	Most influential input variables: Age, cement and water. Unique challenges: Affected by several factors such as size and shape of aggregates and W/C.
Kumar et al. (2023) [31]	FRP-confined concrete	1151	Geometrical metrices, FRP's mechanical properties and C-S	ANN, SVM, GPR, Optimized SVM, Optimized GPR	Optimized GPR (R^2 - 0.9960, MAE - 2.17, RMSE - 3.88.	Most influential input variables: Unconfined C-S of concrete and concrete grade.
Li.D, Z. Tang et al. (2023) [32]	Normal concrete	1030	C, W, FA, CA, SP, blast furnace slag, age, fly ash (8)	GBRT	GBRT (R^2 - 0.92, RMSE - 4.7, MSE - 22.09)	Most influential input variables: Age and cement. When compared with ANN, SVM, RF and Adaboost, GBRT outperformed. Complex composition and non-linear relationships are difficult. It is simple and convenient for engineers as a black box model
S. S. Pakzad et al. (2023) [33]	SFRC	176	Water - Cement ratio (W/C), C, FA, SP, flyash, characteristics of hooked industrial steel fibers	CNN, KNN	CNN (R^2 - 0.928, MAE - 3.833, RMSE - 5.043)	Most influential input variables: W/C, FA, SP, flyash, and cement. Comparative performance CNN > SVR > KNN. Limitations include need for extensive data collection and potential for overfitting.
S. Nazar et al (2022) [34]	Nano modified concrete	94	C, W/C, FA, CA, CNT %, NS %, Nano clay %, Nano alumina %	DT Technique and RF Technique	RF (R^2 - 0.96, MAE - 3.253, RMSE - 4.387)	Most influential input variables: C, W/C, FA, CA. RF Technique outperforms DT Technique and GEP in accuracy and efficiency
R. Gayathri et al. (2022) [35]	Cement mortars with and without metakaolin.	424	Age, Cement grade, Metakaolin/ total binder ratio, Superplasticizer/ binder ratio, Water/ binder ratio (W/B), Binder/ sand ratio.	LR, RF Regressor, SVR, Ada Boost Regression, MLP, GBR, DT Regression, Hist GBR (hGBR), XGBoost Regression	XGBoost regression	Most influential input variables: Water-to-binder ratio XGBoost regression is the best model, followed by hGBR, SVR, GBR, DT, RFR, MLP, ABR, and LR. Non-linearity in the data makes simple statistical models insufficient.

Torkan Shafighfard et al (2022) [36]	SFRC	307	-	SVM, RF, GBM, Extra Tree Regression, KNN	SVM, RF, GBM, KNN & extra tree regression. (Approximate all R^2 - 0.92)	Use of a stacked ML pipeline with multiple algorithms. SVM, RF, extra tree regressor, GBM and KNN accurately predicts C-S of SFRC subjected to high temperatures.
S. Shah et al (2022) [37]	Sustainable concrete (flyash and blast furnace slag)	1030	Ordinary Portland cement (OPC), flyash, blast furnace slag, W, age, SP, FA, CA	ANN and DT	DT models (R^2 - 0.943 & 0.836) ANN models (R2 - 0.873 & 0.848)	OPC content and curing age are the most potent variables. Complexity of interactions between multiple input variables Further validation and ML models training with detailed experimental setups are needed.
Aman Kumar et al (2022) [38]	Light weight Concrete	120	C, W, FA, normal weight CA, light weight CA and W/C.	GPR, SVM Regression, Ensemble Learning and their optimized versions	optimized GPR (R = 0.9803)	Most influential input variables: C, W, FA, normal weight CA, light weight CA and W/C. Optimized GPR > Optimized SVMR > GPR > SVMR > Optimized EL > EL.
S. Chithra et. al (2016) [39]	HPC with Nano silica & Copper slag	-	C, SP, FA, CA, W, nano silica content, copper slag content, specimen age and experimental C-S	Multiple Regression Analysis (MRA) and ANN	ANN attains better accuracy	RMSE and MAPE has very low value

** CatBoost – Category Boosting, CNN – Convolutional Neural Network, CNT – Carbon Nano Tubes, FRP – Fibre Reinforced Polymer, GBM – Gradient Boosting Machine, GBR – Gradient Boosting Regression, GBRT – Gradient Boosting Regression Tree, GEP – Gene Expression Programming, GPR – Gaussian Process Regressor, KNN – K-nearest Neighbor, LR – Linear Regression, MLP – Multi-Layer Perceptron, MLR – Multiple Linear Regression, NS – Nano silica, RT – Regression Tree, SFRC – Steel Fiber-Reinforced Concrete, SVR – Support Vector Regressor.

The results of C-S obtained from different ML models like ANN, SVM, RF, Adaboost regressor, BR and so on in various studies, which was reviewed through the evaluation metrices namely, R^2, MAE, MAPE and RMSE are shown in the table no - 2 and individual results shown in fig. 1 – A, B, C and D respectively.

Table.2 – Evaluation metrices value of different ML models in various C-S prediction studies

Paper Ref.	Model	Data set Size	MAE	MAPE	R^2	RMSE	Concrete Category
Yang Yu et.al (2018) [22]	SVM	1761	5.950	22.991	0.793	1.8835	HPC
	ANN		5.038	19.019	0.960	1.4449	
	SVM with CSO		3.98	14.013	0.942	1.0463	
J. Xu et. al (2019) [40]	ANN	2817	-	15.13	-	7.71	Normal and high strength recycled concrete
Qinghua H et. al (2019) [23]	RF	1030	3.106	11.785	0.966	4.4339	HPC
De-Cheng Feng et.al (2020) [24]	AdaBoost	1133	1.43	4.3	0.952	1.93	Normal Concrete
Ayaz Ahmad et.al (2022) [25]	BR	-	1.51	-	0.97	1.94	Fly ash based Geopolymer Concrete
	AdaBoost		2.16		0.94	2.62	
	DT		2.62		0.90	3.38	

M.Z. Naser (2023) [27]	BigML	1030	2.79		0.92	-	UHPC
	Dataiku		3.69		0.924	4.791	
	DataRobot		3.12		0.937	4.363	
	Explanatory		-		0.925	4.350	
	RapidMiner		-		0.954	3.543	
H N Muliauwan (2020) [41]	LR	1030	8.634	31.69	0.768	10.975	HPC
	ANN-LR		6.504	24.35	0.876	8.319	
	SVM-LR		8.607	32.32	0.774	10.862	
	ANN-SVM		6.622	25.29	0.883	8.360	
	ANN-SVM-LR		7.103	26.99	0.855	9.039	
Vimal R (2022) [42]	GBR	1030	2.73	-	0.96	3.40	HPC
Satish P (2023) [30]	XGBoost Regressor	633	2.13	-	0.95	3.06	Fly ash Concrete

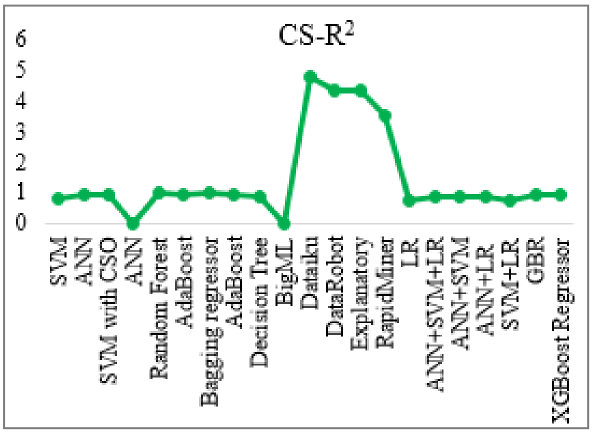

Figure 1A. R² value of different ML models used in various studies to determine C-S.

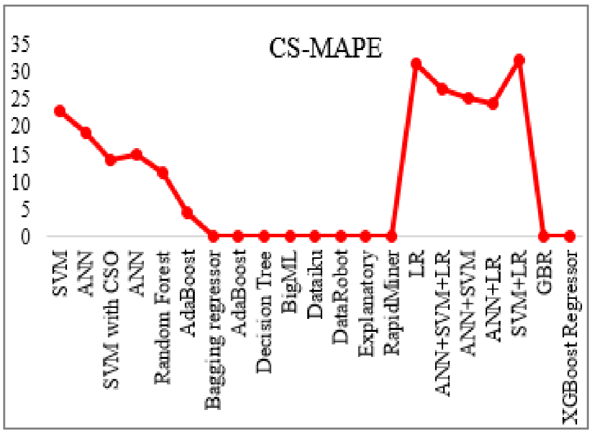

Figure 1C. MAPE value of different ML models used in various studies to determine C-S.

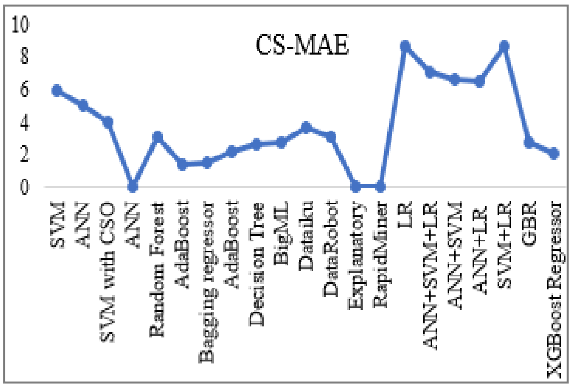

Figure 1B. MAE value of different ML models used in various studies to determine C-S.

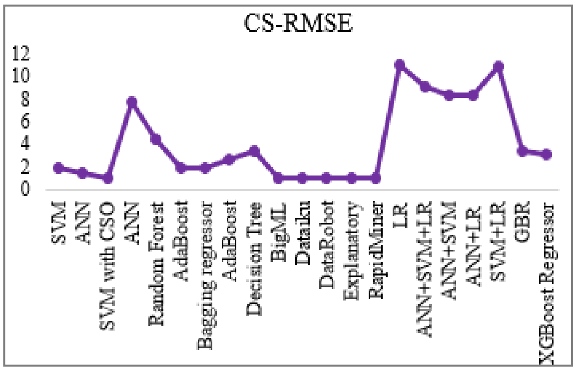

Figure 1D. RMSE value of different ML models used in various studies to determine C-S

Fig. 1: A, B, C and D – R2, MAE, MAPE and RMSE value of different ML models used in various studies to determine C-S.

Figure – 1 (A, B, C, D) shows the performance of various ML models in computing C-S of different concrete type through the evaluation metrices particularly R^2, MAE, MAPE and RMSE respectively. The graph demonstrates LR and hybrid model of ANN possess higher value of MAE, MAPE and RMSE, but the R2 value were low on those models.

Through the analysis, the ML models are more effective for computing the C-S of both traditional and new concrete types, including geopolymer concrete, UHPC, FRP-confined concrete and fiber-reinforced systems. Across the reviewed literature, ensemble-based algorithms such as RF, LightGBM, XGBoost and CatBoost consistently achieve higher accuracy and better generalization than traditional regression and standalone ANN models. While ANN remains widely adopted, its performance varies considerably with network architecture, dataset size and hyperparameter tuning. In contrast, tree-based ensembles show stable performance across heterogeneous datasets and require less calibration. Studies on new concretes highlight limited transferability of models trained on normal concrete, emphasizing the importance of domain-specific training data. Furthermore, ensemble models offer improved interpretability through feature-importance analysis, enabling identification of dominant parameters namely W/B ratio, curing age, and supplementary cementitious materials. Overall, ensemble learning provides the best and balance between accuracy, robustness, and interpretability for C-S prediction.

2.2. Shear Strength

De-Cheng Feng et.al (2021) introduced the ensemble methods to estimate the shear strength of reinforcement deep beams with or without web reinforcements. Ensemble models like RF, AdaBoost, GBR tree and XGBoost were adapted in this study. Then the model was validated by 10-fold cross validation method and find out the model performance. The grid search method was utilized to determine the persistent parameters predicting the shear strength and compared with classical models. From the results of four models, the XGBoost model showed the better result. [43]

Odey Alshboul et.al (2023) evaluated the shear characterisations of stirrups free SFRC deep beams through ML models. In contemporary models, the regression model was used to predict shear strength of RC beams due to their complexity of concrete response to shear stress. Again, the steel fibers were incorporated in the concrete which become more complication to calculate shear strength of SFRC deep beams. It is complicate to solve through traditional codal provision. The complexity of the calculation of shear strength was addressed through LGBM, XGBoost and GEP. The R^2 values of LGBM and XGBoost were 97.8% and 94.5% respectively, which was more accurate than the GEP [44].

Ataollah Taghipour Anvari et.al (2023) assessed the evolutionary machine learning approach through genetic programming (GP) method to calculate shear strength of FRP incorporated with RC beams. The authors developed two GEP model such as Model – I and Model – II by varying the input parameters like span to depth ratio, effective depth, minimum width of cross section, concrete C-S, yield strength of shear reinforcement, young's modulus of FRP, effective strain of FRP, FRP area fraction and shear reinforcement ratio and shear strength of FRP as output parameter. Its accuracy and performance were analysed by using R^2 and RMSE. The GEP models were developed depends on the basis of three datasets namely, first sets – RC beams with and without shear reinforcement, second sets – RC beams without shear reinforcement and third sets – RC beams with shear reinforcement. Then the comparative study of GEP models indicated higher accuracy with already exist models. The researchers also concluded that the GEP models developed in this paper estimated the shear strength of RC beams without assumptions unlike other existing modelling methods. These generated models I and II can be helped to avoid the estimation of shear strength of RC beams with FRP sheets through conventional experiment methods [45].

Jesika Rahman et.al (2023) enhanced the eleven ML models namely, lasso regression, LR, ridge regression (RR), RF, SVM, DT, KNN, ANN, CatBoost, AdaBoost, and XGBoost by data driven approach to find shear characterisation of RC beams with steel fibers. The concrete C-S, shear span/ effective depth ratio, type of fiber, longitudinal reinforcement ratio, aspect ratio and volume fraction of fiber to predict shear strength are adapted as input variables. The XGBoost model performed well in anticipating with highest accuracy in terms of R2 and lowest in RMSE and MAE and influenced by the input features such as shear span/ effective depth ratio, concrete C-S, volume fraction of fiber and longitudinal reinforcement ratio [46].

Thushara Jayasinghe et.al (2023) adapted the ML models including LR, LGBM, KNN, Gradient Boosting (GB), RF, XGBoost, CatBoost, and AdaBoost to calculate the shear strength of recycled aggregate concrete. The researchers adopted two different types of samples such as slender beams and deep beams. Those datasets are selected based on the criteria as three-point and four-point loading of rectangular beams, considered only shear failures no flexural failure and RAC beams with or without shear reinforcements were adopted. The input features are divided into four categories namely, geometry characteristics: effective depth, shear span/ depth ratio, beam height, beam width. Concrete property: replacement ratio RCA, maximum size of recycled aggregate, water/ cement ratio (W/C), C-S of concrete. Longitudinal reinforcement: yield strength and reinforcement ratio. Transverse reinforcement: yield strength and reinforcement ratio and output variable as shear strength. The XGBoost showed the better performance with R2 of 0.95 and 0.78 for slender beams and deep beams respectively. Hence, this model was taken to further analysis for parametric analysis and feature performance through Shapley additive explanations (SHAP) and compared with codal provisions in different countries including AS3600-2018, ACI381-19, GB50010-2010 and Eurocode 2. The SHAP result indicated that the replacement ratio has minimum influence on shear strength value [47].

Table.3 – summary of recent ML based studies on shear strength prediction - highlighting commonly used algorithms, relative performance and key insights across conventional and new concrete types.

Authors (Year)	Concrete Type	Data set Size	Input parameters	ML Models Used	Best Model	Key insight
Khaled Megahed (2024) [54]	RC Deep Beams	840	Geometric dimensions, concrete properties, longitudinal reinforcement properties, web reinforcement properties, plate widths	Symbolic regression, XGBoost, CatBoost, RF, LGBM, SVR, ANN, GPR	CatBoost (R^2 - 0.947)	Most influencing input variables: Span/ depth ratio, concrete C-S, and reinforcement ratios. Critical input features: Concrete strength, reinforcement ratios, and beam dimensions. CatBoost is high in handling features categorical and has high generalizability, symbolic regression offers simplicity and robustness.
B. R. Hassan et al (2024) [55]	FRC beams with longitudinal FRP bars	-	Fibre type, bar diameter, concrete C-S, beam dimensions	MLR, RF Regressor, GPR, KNN, SVM, ANN	-	Most influencing input variables: fibre type, bar diameter, concrete C-S, beam dimensions.
O. Alshboul et al (2024) [56]	SFRC	333	Beam width, longitudinal steel reinforcement ratio and beam depth effect	LGBM, XGBoost, GEP	LGBM (R^2 – 0.957, RMSE – 20.04)	Most influencing input variables: beam width, longitudinal steel reinforcement ratio and beam depth effect. GEP considers important factors like beam depth and longitudinal steel reinforcement ratio, combining classic engineering approaches with ML strategies can improve accuracy and reduce bias.
Meng Ye et al (2023) [57]	UHPC	-	Geometric dimensions, shear span/ depth ratio, reinforcement parameters, material properties of UHPC	CatBoost	CatBoost	Ensemble models enhanced than individual ML models and conventional empirical methods. Most influencing input variables: Geometric dimensions, shear span/ depth ratio and then reinforcement parameters and UHPC's material properties.
M. Sandeep et al (2023) [53]	RC beams Conventional, SFRC and HSC	-	C-S, effective depth, strength of transverse reinforcement, section width, shear span/ depth ratio	ANN, ANFIS, RF, SVR, XG Boost	XGBoost and RF	Critical input features: C-S, cross-sectional details, span/ depth ratio.
G. Almasabha et al (2023) [49]	Synthetic FRC beams without stirrups	102	Fiber's volume ratio, effective depth, shear span/ depth ratio, beam width, longitudinal reinforcement ratio, concrete C-S	LGBM, XGBoost, GEP	LGBM (R2 – 0.9891)	Critical input features: Fiber's volume ratio, effective depth, shear span/ depth ratio, beam width, longitudinal reinforcement ratio, and concrete C-S.

Z. Yaseen (2023) [58]	FRP reinforced concrete	112	Effective depth, beam width, shear span/ effective depth ratio, concrete C-S, longitudinal and transverse reinforcement ratio, E value for longitudinal reinforcement and transverse reinforcement, tensile strength of transverse stirrups.	M5-Tree, ELM, RF	M5-Tree model (R^2 - 0.9313 RMSE - 35.5083)	Beam dimensions and stirrups are more critical input features. RF model is reliable with fewer parameters. ELM requires more parameters to increase performance. Tree-based models are effective for capturing nonlinear relationships with limited parameters.
Aman Kumar et al (2023) [59]	Corroded RC beams	140	Beam width, effective depth, shear span/ depth ratio, concrete C-S, yield strength of longitudinal reinforcement and stirrups, % of longitudinal and transverse reinforcement, stirrups spacing, corrosion degree of stirrups1, corrosion degree of main reinforcement.	ANN, ANFIS, DT, XGBoost	XGBoost (R^2 - 0.9998)	Most Influencing Input Variables: Effective depth, shear span/ depth ratio and stirrups spacing. Need for larger datasets and development of a GUI for practical application.
Celal Çakıroğlu, G. Bekdaş (2023) [60]	RAC	128	C-S, effective depth, beam width, shear span/ effective depth ratio, RCA %, longitudinal reinforcement ratio.	XGBoost, Extra Trees Regressor	XGBoost (R^2 – 0.94)	Beam width was the most influencing input variable. Need larger datasets for practical application.
A. Ebid et al (2022) [61]	Normal-weight and lightweight concrete	1700	Beam width, effective depth, concrete C-S, shear span, longitudinal reinforcement ratio, Specific gravity of concrete, maximum nominal size of aggregates.	EPR, ANN, GP	ANN (83% accuracy)	Beam dimensions and shear span are the most influencing input parameters.
Amjed Shatnawi et al (2022) [62]	Steel Fiber Reinforced Concrete	330	Effective depth, beam width, concrete C-S, shear span/ effective depth ratio, longitudinal reinforcement ratio, aggregate size, fiber tensile strength, steel fiber factor.	GBRT	GBRT (R^2 - 0.9692, RMSE < 30, MAE < 17, MAPE < 14%)	Effective depth, beam width, concrete C-S & ratio of longitudinal reinforcement are the most influencing factors.
Md Nasir Uddin et al (2022) [63]	RC beams	201	Effective depth, Shear span, concrete C-S, web width, yielding strength of longitudinal and transverse reinforcement, longitudinal reinforcement ratio and transverse reinforcement ratio.	GBR, RF	GBR (R^2 - 0.985) & RF (R^2 - 0.98)	GBR, RF, and ANN showed higher accuracy compared to MLR and ridge regression (RR). Most critical input features: C-S, shear span, web width, effective depth, and reinforcement ratios.

** ANFIS – Adaptive Neuro-Fuzzy Inference System, E – Modulus of Elasticity, ELM – Extreme Learning Machine, EPR – Evolutionary Polynomial Regression, FRC – Fibre Reinforced Concrete, HSC – High Strength Concrete, LGBM – Light Gradient Boosting Machine, RAC – Recycled Aggregate Concrete, RC – Reinforced Concrete, RCA – Recycled Concrete Aggregate.

The results of shear strength obtained from different ML models like ANN, SVM, RF, Adaboost regressor, BR and so on in various studies, which was reviewed through the evaluation metrices namely, R^2, MAE, MAPE and RMSE are shown in the table no - 4 and individual results shown in fig. 2 – A, B, C and D respectively.

Table 4. Evaluation metrices value of different ML models in various shear strength prediction studies

Paper	Model	Dataset Size	R^2	MAE	RMSE	MAPE	Concrete Category
De-Cheng Feng et.al (2021) [43]	DT	271	0.887	42.56	63.145	14.41	Normal Concrete
	SVM		0.852	40.26	72.020	11.76	
	ANN		0.856	52.05	71.111	18.13	
Odey Alshboul et.al (2023) [44]	Light GBM	172	0.978	0.248	0.369	4.9	Steel Fiber Reinforced Concrete
	XGBoost		0.945	0.319	0.576	5.8	
	Gene Expression		0.789	0.963	1.241	22.4	
Ataollah T. et.al (2023) [45]	GEP	785	0.940	-	0.33	-	FRP Concrete
Jesika R. et.al (2023) [46]	XGBoost	507	0.739	0.704	1.346	-	Steel Fiber Reinforced Concrete
Thushara J. et al (2023) [47]	XGBoost with SHAP	401	0.95	0.11	0.161	0.084	Recycled aggregate concrete
Jesika Rahman et.al (2023) [48]	*Rectangular Beam:* CatBoost	302	0.629	0.214	0.378	-	FRP Concrete
	XGBoost		0.642	0.202	0.371	-	
	T-Beam: CatBoost		0.964	0.127	0.181	-	
	RF		0.963	0.128	0.184	-	
Ghassan Almasabha et.al (2023) [49]	LightGBM	102	0.989	11.83	14.20	8.82	Synthetic Fiber Reinforced Concrete
	XGBoost		0.972	18.26	23.35	10.13	
	Gene Expression		0.882	113.33	148.16	78.97	
Siyuan Wang et.al (2023) [50]	*Hold out:* Gaussian process regression (GPR)	395	0.924	0.5262	0.491	-	Steel Reinforced Concrete
	Bootstrapping: GPR		0.941	0.4861	0.4553	-	
Cailong Ma et.al (2023) [51]	DT	457	0.815	0.842	1.274	-	Reinforced concrete (RC)
	RF		0.884	0.699	1.010	-	
	XGBoost		0.917	0.531	0.777	-	
Cailong Ma et.al (2023) [52]	XGBoost with SHAP	774	0.953	0.220	0.328	10.951	RC
Sandeep M.S. et.al (2023) [53]	XGBoost RF ANN	271	0.722	-	-	-	RC

Figure – 2 (A, B, C, D) shows the anticipation capacity of different ML models in computing shear strength of different concrete type through the evaluation metrices particularly R^2, MAE, MAPE and RMSE respectively. The graph demonstrates the gene expression, SVM, decision tree and ANN models possess higher value of MAE, MAPE and RMSE, but the R^2 value were more or less similar for all the models and lower value in XGBoost algorithm.

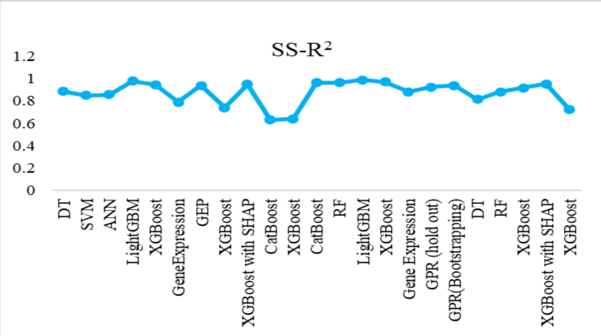

Figure 2A. R^2 value of different ML models used in various studies to determine shear strength

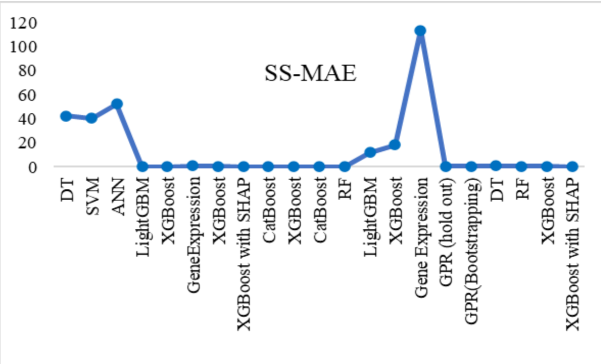

Figure 2B.MAE value of different ML models used in various studies to determine shear strength

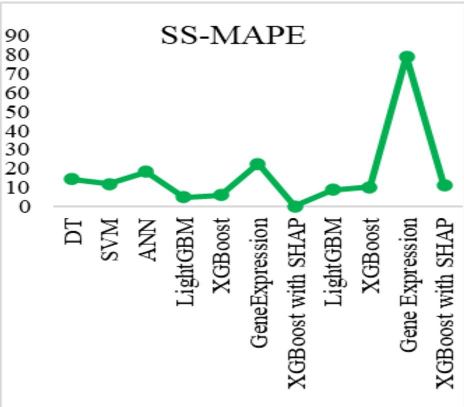

Figure 2C.MAPE value of different ML models used in various studies to determine shear strength

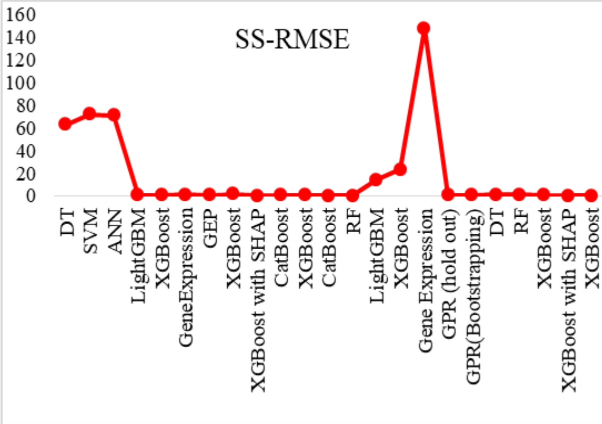

Figure 2D. RMSE value of different ML models used in various studies to determine shear strength

Fig. 2: A, B, C and D – R2, MAE, MAPE and RMSE value of different ML models used in various studies to determine shear strength.

On the whole, recent research confirms that ML models significantly improve shear strength prediction of reinforced concrete elements including rare systems such as UHPC beams, SFRC beams, GFRP-reinforced members, corroded RC beams, FRP-confined columns, etc. Ensemble learning algorithms particularly, RF and gradient boosting model consistently show superior predictive performance compared to empirical code equations and standalone ML techniques. These models effectively handle complex geometric, material, and reinforcement parameters governing shear behavior. Hybrid optimization-based models occasionally yield marginal accuracy improvements on large datasets but suffer from reduced interpretability. In contrast, tree-based models combined with explainable AI tools provide meaningful insights into dominant shear features such as shear span/ depth ratio, transverse reinforcement, amount of fiber and confinement effects. Several studies report poor transferability across different structural systems, highlighting the necessity for dataset-specific training. Overall, ensemble ML models with interpretability enhancements represent the most practical approach for shear strength prediction.

Despite strong predictive performance, most ML models suffer from limited generalization across concrete types, highlighting the need for domain-specific datasets and physics-informed learning frameworks.

3. SUMMARY AND CONCLUSION

The present researches focused on the application of ML models in concrete technologies, particularly in concrete properties like C-S, shear strength, flexural strength and so on. This work mainly concentrated on compressive strength and shear strength. ML models (XGBoost, decision tree, random forest, LGBM, SVM, ANN and so on) and validation methods (10-fold cross validation method, k-fold validation techniques) are employed for the concrete property's estimation in the different studies, which has the datasets and parameters handled are limited in nature. The major parameters used to analyse the compressive strength through cement, water, CA, FA, super plasticizer, curing age and for the shear strength, the shear span/ depth ratio, effective depth, C-S of concrete, yield strength of shear reinforcement, width of cross section, young's modulus are taken. The performance of analyzation and validation are confirmed through the evaluation metrices and compared with the convention methods.

In lights on the analyse, ANN, RF, XGBoost, and SVM models delivered precise results on compressive strength and shear strength. The interpretation of input variables in various models is lower because of limited datasets. The implementation of ML models in industrial space is difficult due to almost in absence of datasets of structures in a natural environment. Numerous ML models were adopted in this field but the research is limited to the specific concrete type (HPC, Flyash based concrete, UHPC, etc) and few concrete properties. The researchers must focus on other concrete types like geopolymer concrete, green concrete and other supplementary material concretes and also develop models for field datasets. It can able to save the time and resources, increase the interpretation of complex nonlinear - input parameter relationships and create the base for incorporation in industries.

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IZVOD

ANALIZA SVOJSTVA BETONA KROZ MODELE MAŠINSKOG UČENJA

Modeli mašinskog učenja (ML), najistaknutije metodologije, sada se koriste u praktično svim oblastima za rešavanje teških i složenih problema bez kodiranja. ML se nedavno koristi u ogromnim primenama u građevinarstvu, uključujući analizu troškova tokom faze izgradnje, upravljanje radnom snagom na gradilištu, praćenje zdravlja konstrukcija i životnog ciklusa zgrade, upravljanje građevinskim otpadom, analizu mehaničkih svojstava (kompresivna, aksijalna čvrstoća, itd.), čvrstoće na smicanje i ugradnju različitih vlakana/polimera/otpada od rušenja u beton. Ovaj pregledni rad istražuje primene ML modela, posebno XGBoost, ANN, RF i SVM, koji se koriste za najpreciznije predviđanje vrednosti svojstava betona (kompresivna i čvrstoća na smicanje). Interpretacija ulaznih varijabli u različitim modelima je smanjena zbog ograničenih skupova podataka. Primena ML modela na radnim mestima je izazovna zbog oskudice skupova podataka koji se odnose na konstrukcije u prirodnim okruženjima. U ovom radu su takođe razmotrene praznine u znanju i preporuke za unapređenje istraživanja.

Ključne reči: *Mašinsko učenje, svojstva betona, mehanička svojstva, čvrstoća na smicanje.*

Naučni rad
Rad primljen: 02.05.2025.
Rad korigovan: 29.12.2025.
Rad prihvaćen: 29.03.2026.

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