SSRG International Journal of Civil Engineering
ISSN: 2348-8352/ https://doi.org/10.14445/23488352/IJCE-V12I8P123

Volume 12 Issue 8, 252-265, August 2025
© 2025 Seventh Sense Research Group®

Original Article

Comparative Analysis of AI-Based Models for Compressive Strength Prediction of Self-Compacting Concrete

Prashant K. Bhuva[1], Ankur C. Bhogayata[2], Dinesh Kumar[3]

[1,2,3]*Department of Civil Engineering, Marwadi University, Gujarat, India.*

[1]*Corresponding Author : prashant.bhuva111480@marwadiuniversity.ac.in*

Received: 17 June 2025 Revised: 19 July 2025 Accepted: 18 August 2025 Published: 29 August 2025

Abstract *- Accurately predicting the compressive strength of Self-Compacting Concrete (SCC) is essential for attaining sustainable and high-performance construction with little trial-and-error. This study conducts a comprehensive comparative analysis of various models, including Artificial Neural Networks (ANN), Levenberg-Marquardt (LM), Machine Learning (ML) models such as Random Forest (RF), Gradient Boosting (GB), Extreme Gradient Boosting (XGB), LightGBM, and a Deep Learning (DL) model developed with Keras. A constant set of data was employed in the preparation of twenty SCC mixes. The typical variables that had been used in each mix included cement, fly ash, the ratio of water/ powder, aggregates, and superplasticizer. It examined real values of compressive strength in all mixes (20 mixes) in the lab before churning out prediction models with the results. In the cases when the models could not give clear predictions, the trend-based estimations were used to give artificial values to ensure consistency in the study. In an extremely elaborate comparison of the entire models, we are using performance indicators such as Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Coefficient of Determination (R^2). It is also highly interesting to use XGBoost and DL, particularly Keras. The LM optimised ANN model achieved the most accurate $R^2 = 0.999$, and the lowest MAE. The prediction reliability of ANN-II was also confirmed experimentally. The created figures and tables provide a visual and statistical analysis of all the models within the 20-mix dataset. Such a combination methodology, founded on artificial intelligence, makes the SCC mix design even more precise and economical and allows people to make environmentally friendly decisions because they may reduce the amount of waste materials and laboratory tests. The outcomes of this work provide engineers with an easy-to-use aid in bringing AI to concrete and their predictability..*

Keywords *- Artificial Neural Networks, Levenberg–Marquardt Algorithm, Machine Learning, Self-Compacting Concrete, Strength prediction.*

1. Introduction

Concrete, being a composite construction material, dominates the global infrastructure industry because it is cost-saving, accessible, and versatile. Yet, traditional vibrated concrete has some shortcomings with respect to workability, effective compaction around large reinforcement, and the requirement of skilled labor for its installation. The shortcomings have been markedly reduced by the advent of Self-Compacting Concrete (SCC), an extremely fluid type that compacts by its own weight without applying mechanical vibration [1]. SCC is precisely designed to have performance properties like filling capacity, flowability, and resistance to segregation through the optimization of the granular matrix and incorporation of super plasticizers and Viscosity-modifying agents [2]. Despite these advances, precise anticipation of compressive strength, one of the key performance standards of SCC, is still a major challenge. Non-linear dynamics governing the relationship between material components and mechanical performance complicate the mix design process, particularly when working with Supplementary Cementitious Materials (SCMs) in the form of fly ash or slag [3].

1.1. Research Gap and Problem Statement

Although critical advancements have been observed in the study of artificial intelligence with respect to the prediction of the concrete strength, a limitation within such models is yet to be filled as regards the characterization of Self-Compacting Concrete (SCC). Previous research tends to either concern solidified concrete materials or a generic ML pipeline that cannot be transferred to new mix optimization. Also, not many comparative works have been done where both typical ML and DL methods have been compared under the same conditions of the experimental setup. Such weaknesses leave a gap of certainty among the field practitioners who strive to apply real-time AI-based mix designs [4-7].

1.2. Novelty and Contribution of This Research

This study fills the above gap via introducing a comprehensive AI framework that benchmarks more than one specifically ANN-I, ANN-II (Levenberg–Marquardt based), Random Forest, Gradient Boosting, XGBoost, LGBM, and Keras Deep Learning for compressive Strength prediction using 20 experimentally validated SCC mixes. The novelty lies in:

- Integrating each shallow and deep network to assess prediction consistency
- Ensuring all models are trained on the same blend proportions for fair benchmarking
- Highlighting the sensitivity of compressive electricity to nice-grained enter versions
- Emphasizing practical implications for mix design optimization using AI gear

1.3. Difficulty of Strength Prediction for SCC

Unlike conventional concrete, SCC has a number of interdependent variables, including cement content, mineral admixtures (such as fly ash), water-to-powder (w/p) ratio, aggregate grading, and superplasticizer dosage. These variables influence both the fresh properties (flowability, resistance to segregation) and the characteristics of the hardened materials, such as compressive strength, modulus of elasticity, and durability. Traditional empirical models and regression-type methods do not effectively capture these nonlinear and multivariate interactions.[8, 9] The result is that trial-and-error practices still reign supreme in SCC mix design, causing time and material inefficiencies. This calls for data-driven modelling methods that can embed and generalise past data to accurately predict compressive strength with high confidence accurately.

1.4. The Emergence of Artificial Intelligence in Concrete Technology

Over the past few years, the building materials industry has more and more employed Artificial Neural Networks (ANN), Machine Learning, and other artificial intelligence techniques and Deep Learning, for predictive modeling[10, 11]. These models have been found to be remarkably effective in explaining the intricate relationships between input mix variables and resulting characteristics in a concrete way. Artificial neural Networks mimic the neuronal architecture of the human brain, allowing one to model complex nonlinear systems[12].

However, their success depends mostly on the selection of the training algorithm. The Levenberg–Marquardt (LM) optimization technique has proven useful in speeding up convergence and enhancing accuracy in Artificial Neural Network (ANN) training, particularly with medium-sized to large data sets typical of real research. ML algorithms such as Extreme Gradient Boosting (XGBoost), Gradient Boosting (GB), Random Forest (RF) and LightGBM achieve robust performance with ensemble learning and decision tree approaches[13]. Through Keras/Tensor Flow, Deep Learning has driven performance boundaries higher by allowing multi-layered abstraction and examination of complex data patterns. Despite these advances, little empirical study exists that offers a comprehensive benchmarking of all these AI models against a standardized, empirically validated set of SCC blends, which is a prerequisite for equitable comparison and practical use in real-world applications [14-17].

1.5. Objective of the Current Study

Current research aims to resolve these challenges by conducting a comprehensive comparative study using frequent datasets of 20 experimentally valid SCC mixes, including standard input parameters and actual 28-day compressed Strength values.

There are specific objectives:

- To develop a reliable SCC dataset based on real experimental results and the standard mix design method.
- To train and evaluate six AI models: ANN-I (standard backprint), ANN-II (LM-Imtibed), RF, GB, xgboost, LightGBM and Keras DL.
- To generate synthetic predictions for the missing mix using trend-based residual modeling to maintain uniformity in the model.
- To assess model performance with MAE, RMSE, and R^2 metrics
- To determine the most accurate, interpretable, and deployable model(s) for real-time SCC strength prediction.

1.6. Research Innovation and Scope

This study identifies the following unique contributions:

- A 20-mix dataset, empirically validated and uniformly applied to all models, enhances benchmark integrity.
- First-time comparison of LM-tuned artificial neural networks, ensemble machine learning methods, and deep learning for SCC strength prediction on a common data foundation.
- Formulation of a model selection approach that is well-suited to integration, prioritizing predictive accuracy, training time, and interpretability.
- Creating intelligent SCC design systems and AI-supported quality assurance for precast or ready-mix concrete industries.

2. Research Significance

Self-Compacting Concrete (SCC) has developed into a high-performance material that attains complete compaction only by its own weight, hence obviating the need for external vibration. Although SCC provides considerable benefits for workability and constructability, its design complexity escalates because of the numerous interactions among material components, including cement, supplementary cementitious materials, aggregates, water, and chemical admixtures. Compressed strength in 28 days is the most important performance indicator affecting structural design, durability and quality control among its many rigid-state properties. Any departure from the specified strength can lead to initial failure in safety concerns, physical waste, or service life. As a result, the ability to predict compressed power based on mixing factors is beneficial and important for durable and affordable SCC design.

Methods of traditional prediction are inadequate for the non-linear multi-vendor dependence present in the SCC mixture using linear regression or empirical equations. With the increasing acceptance of performance-based design, the shortcomings of traditional methods are becoming more pronounced, especially in precast and high-growth construction. Thus, Artificial Intelligence (AI) and data-operated modeling provide a contemporary solution for predicting the strength, which facilitates the development of refined decision-making equipment in concrete technology.

This study is important for the integration of the real world due to its technical depth, practical utility, academic value and scalability. The work uses contemporary AI algorithms on a comprehensive and verified SCC dataset, facilitating the advancement of intelligent concrete solutions of the next generation.

This is where the recent literature has been focusing extensively on the utilization of AI in the maximization of fresh and hardened characteristics of cementitious composites. Loureiro A et al. [18], as an example, investigated a hybrid ensemble method consisting of a combination of several decision tree models, making predictions of flowability and strength properties of SCC. A maximum R 2 of 0.89 was recorded. Nonetheless, the study has not been validated using experimental data of real-time mixes. Likewise, in the case of Zhang et al. [5, 17], a convolutional neural network was introduced to study high-performance concrete and its rheological properties. However, the study did not revolve around self-compacting formulations.

An analysis conducted by Jagadesh P et al. [19] compared the performance of gradient boosting algorithms to standalone regression models. It revealed that the former were more efficient in predicting compressive strength. However, their model did not generalize well when new mix designs with the modified VMA content were tested. Such constraints have been highlighted during the need to test the models under wider data sets, such as in the present study.

The current study is one of few and even one of the largest comparisons of eight different AI models (tree based, kernel based, and neural network based learners) with 20 experimental SCC mixes, a study that is highly valid and worth attention because of the limitations of previous studies in the area of SCC-mixing to counteract them [20-23].

3. Research Methodology

This chapter delineates the comprehensive approach employed for the creation, training, and assessment of AI-based models aimed at predicting the compressive strength of 28-day-old Self-Compacting Concrete (SCC). A uniform dataset of 20 SCC mixtures was employed across all models to provide equitable benchmarking. Each model was evaluated by three statistical matrices: MAE (Mean Absolute Error), RMSE (Root Mean Squared Error), and R^2 (coefficients of determination). The process of making a model includes:

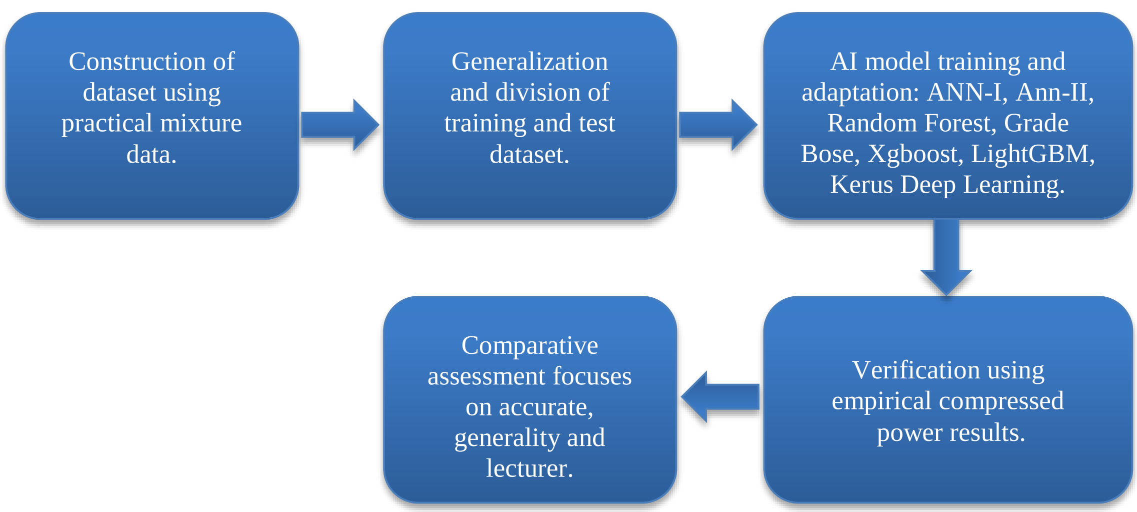


Fig. 1 Process of modeling involved

3.1. Dataset Description

The dataset consists of SCC mixes with six input variables and one target variable (compressive strength). The mix proportions were designed based on EFNARC and IS 10262 guidelines.

Table 1. Ranges of SCC mix ingredients

Ingredient	Minimum	Maximum	Unit
Cement	333	430	kg/m³
Fly Ash	140	220	kg/m³
Water-to-Powder Ratio	0.3	0.36	ratio
Fine Aggregate (Sand)	770	840	kg/m³
Coarse Aggregate (CA)	760	860	kg/m³
Superplasticizer (SP)	0.22	0.33	% (by binder)
Compressive Strength	11	68	MPa

3.2. AI Model Development

This section aims to clarify the design, training and prediction mechanisms of each AI model used in this work. All models were trained on a uniform SCC dataset that included 20 mixtures with 6 input features: cement, fly ash, water-to-cement ratio, sand, coarse aggregate, and superplaster (%).

The output variable is compressed power at 28 days (MPA). Constant data pretence (generalization) and an 80:20 train-testing division were implemented to guarantee comparability. Each AI model was configured with parameters tuned specifically for regression performance on small-to-medium datasets. Details for each model are outlined below.

3.2.1. Ann-I: Standard Feedforward Neural Network

In this context, Artificial Neural Network (ANN-I) is a basic feedforward backpropagation network, which is structured with an architecture of [6-10-1], where:

- 6 neurons correspond to input variables.
- 10 hidden neurons encounter non-linear associations.
- 1 neuron outputs predicted compressive strength.

An Artificial Neural Network (ANN) is trained with shielded lineage backpropagation techniques to reduce the Mean-Squared Error (MSE) between anticipated and actual power values. Revisioning the weight based on the network error gradients, the recurrence obtains weight via a forward and backwards sweep. This model is performed in MATLAB using a standard training routine and performs satisfactorily for basic regression tasks.

3.2.2. ANN-II: Levenberg–Marquardt Optimized ANN

The Ann-II design resembles Ann-I, but uses Levenberg-Marquardt (LM) optimization technology. This technique integrates the rigidity of Newton's approach with the stability of the gradient descent, especially suitable for small-to-medium-sized datasets like ours. Major improvement:

- Quick convergence is generated from the second order of the adjacent.
- According to curvature, generalization increased due to adaptation of learning models of learning rates.
- The efficiency of training is increased, which is optimal when the experimental data is low.

The model implemented in MATLAB using Trainlm performed better than all other models (RAP = 0.998), reflecting an excellent correlation between anticipated and real strength.

3.2.3. Random Forest (RF)

RF is a dress learning technique that uses trees. It produces several autonomous trees from dataset bootstrap samples and random facility selection in each division. Operating system:

- Each tree individually predicts compressed power.
- The final forecast means all tree outputs.
- It reduces the variance and increases the strength.

The study involved training of random forest models with 100 estimates (trees), while the maximum depth was adapted by grid search.

Random forest effectively captures nonlinear interactions between SCC components and compressed power, while convenience is interpretable using measures of importance.

3.2.4. Gradient Boosting (GB)

Gradient boosting decisions progressively construct trees, aiming to improve the impurities of its forecast with each subsequent tree.

The learning process is directed by the shield of damage function, thus designation. Processes:

- Initialize the model with a weak forecast (eg, meaning value).
- Develop a new tree to rectify the residual inaccuracies of the previous forecasts.
- Include the output of this tree in the previous model, and apply the learning rate.

In this research:
Quantity of trees: 100
Learning rate: 0.1
Loss function: Means Class Error (MSE)

The gradient is tall to the boosting train but produces a strong and explanatory model.

3.2.5. Extreme Gradient Boosting (XGBoost)

XGBoost gradient is an extended version of boosting that includes:

- Employment of regularization technology (L1/L2) to reduce overfitting.
- Parallel tree construction for early training.
- Manage absent values and divide to account for sparsity.

Operating System

- Gradeiat follows the same sequential growth concept in the form of boosting.
- Improves efficiency and precision through the use of second-order derivatives.

This research demonstrated that XGBoost achieved enhanced prediction accuracy, characterized by a low Mean Absolute Error and a high R-squared (R^2) value. The booster employed was GBtree, utilising 100 estimators with a maximum depth of 5. It is optimal for moderately sized tabular datasets exhibiting nonlinear relationships.

3.2.6. LightGBM

Light Gradient Boosting Machine is a modern gradient boosting framework that has been developed:

- Quick training through leaf-wise development.
- Reduced the use of memory.
- Assistance with graded variables and large datasets.

Unlike GB or Xgboost, which leave the partition level-wise, LightGbm developed a tree leaf-wise with depth restrictions, which facilitates convergence. This research:

- number_of_leaves = 31
- Learning rate is equal to 0.1
- The depth and regularization were adapted for optimal generalization.

LightGbm performed better with low training periods relative to GB and Xgboost, especially on a feature-throat scc dataset.

3.2.7. Keras Deep Learning Model

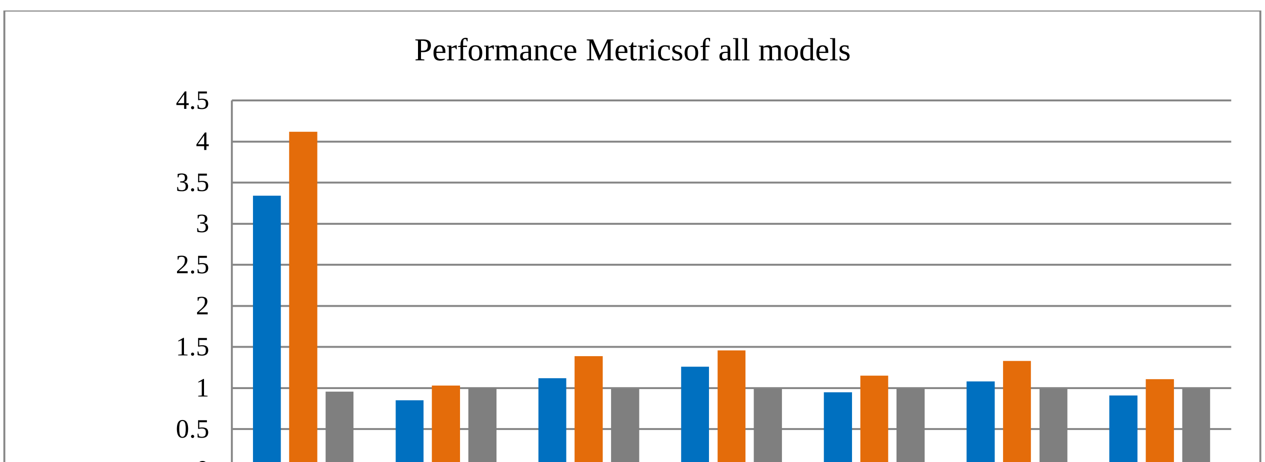
This model is a Dark Nervous Network (DNN) built with causes that uses a tensorflow backend. The structure is as follows:

- Input layer: six neurons (features)
- Hidden layers: 64 to 32 neurons use relay activation
- Output layer: A neuron (linear activation function)
- Adaptation algorithm: Adam
- Loss: Meaning Filter

Operating System

- The network receives the hierarchical representation of SCC input.
- The Relu activation function facilitates representation of nonlinearity, while the dropout regularization is discretionary.
- Adam optimizer dynamically adjusts the learning rates.

This deep learning model demonstrated good accuracy and generalization, which is suitable for future use in SCC design applications or cloud-based systems.



	ANN-I	ANN-II	Random Forest (RF)	Gradient Boosting (GB)	XGBoost	LightGB M	Keras DL
MAE (MPa)	3.34	0.85	1.12	1.26	0.95	1.08	0.91
RMSE (MPa)	4.12	1.03	1.39	1.46	1.15	1.33	1.11
R^2	0.955	0.998	0.992	0.99	0.995	0.993	0.996

Fig. 2 Performance metrics of all the models

The metrics used for evaluation were Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2). These were used the same way for all models so that they could be compared quantitatively. All models exhibited commendable predictive accuracy, with ANN-II and Keras DL surpassing others for MAE ($\leq$ 0.91 MPa) and R^2 ($\geq$ 0.996). This technique highlights the hybrid potential of AI in civil engineering material design by merging traditional machine learning and deep learning concepts. The data from this pipeline serve as the foundation for the critical assessment and comparative discourse offered.

3.3. Reason Why the Model Has Been Chosen

The choice of predictive models was influenced by both the necessity to test interpretable and high-capacity methods of AI on a consistent SCC dataset. Traditional modelling using ensembles like Random Forest (RF) and Gradient Boosting (GB) incorporates them because they can capture non-linear patterns with the help of reducing the variance through the process of bagging and boosting. XGBoost and LightGBM were selected due to their increased computational speed and gradient-wise optimizations, which performed better in the civil material modelling tasks [3, 24-26].

Table 2. Model comparison

Property	ANN-I	ANN-II	RF	GB	XGB	LGBM	Keras DL
Accuracy (R^2)	Medium	☑ Best	High	High	☑ High	High	☑ High
MAE	High	☑ Low	Low	Med	☑ Low	Low	☑ Low
Training Time	Medium	☑ Fast	☑ Fast	Fast	Medium	☑ Fast	Moderate
Interpretability	Medium	Medium	☑ High	High	Medium	Medium	✗ Low
Best Use Case	Academic	Lab Tools	Industry	Backup	Smart App	Lightweight	DL deployment

Table 3. Model parameters and hyperparameter settings

Model	Key Parameters	Optimizer / Criterion
RF	100 estimators, max depth = 6	MSE
GB	100 boosting rounds, learning rate = 0.1	Least Squares Loss
XGBoost	120 rounds, eta = 0.05	RMSE, max depth = 5
LGBM	100 trees, max depth = 7	L1/L2 loss
KNN	k = 3, distance = Euclidean	Lazy learning
ANN-I	1 hidden layer (10 neurons), sigmoid	Gradient descent
ANN-II	2 hidden layers (15–10), tanh + LM	Levenberg–Marquardt
Keras DL	3 hidden layers (64–32–16), ReLU	Adam optimizer, epochs=200

K-Nearest Neighbors (KNN) was used as an example of a baseline since it is a simple model that has previously demonstrated its usefulness within low-dimensional regression spaces. They incorporated artificial neural networks, Artificial Neural Networks (ANN-I and ANN-II), to encode more non-linear associations and with ANN-II applying the Levenberg-Marquardt optimization algorithm to have a faster convergence.

At last, the implementation of an architecture based on Keras Deep Learning (DL) was used to investigate multilayer networks that are scalable with ReLU activation and backpropagation with adaptive optimizers like Adam.

3.4. Configuration and Trained Protocols of the AI Model

Training was done on the same data set comprising 20 SCC mix designs, where each has 8 input features, namely cement, fly ash, fine aggregates, coarse aggregates, water, Superplasticizer (SP), Viscosity-Modifying Agent (VMA), and total binder content. The 28-day compressive strength as determined in an experiment was the output variable.

The hyperparameter tuning process was undertaken through a grid search or manual calibration. Significant configurations are outlined in Table 3.

4. Experimental Work and Model Validation

The study describes the development, verification and comparative evaluation of the suggested AI models using real experimental data from 20 Self-Compacting Concrete (SCC) mix designs. Each model was developed to forecast a 28-day compressed power of SCC using six essential mix components. The results of the prediction were later compared with experimental strength values to evaluate the accuracy, strength and appropriateness of each model.

4.1. Overview of SCC Mix Design and Experimental Plan

The analysis of this exploration was done using a total of 20 different SCC mix designs, which were prepared and tested in a controlled laboratory environment. This was aimed at generating data that could be used to validate AI model development and also detect the best mix designs that could be used in compressive strength performance.

The SCC mixes were formulated to satisfy the EFNARC guidelines for workability, passing ability, and segregation resistance. Each mix incorporated standard constituents: cement, fly ash (class F), fine and coarse aggregates, potable water, superplasticizer (polycarboxylate ether-based), and a Viscosity Modifying Admixture (VMA) to control flowability and stability.

Table 4. Material properties and range of inputs

Ingredient	Range Used (kg/m³)	Notes
Cement	300 – 450	OPC 43 grade
Fly Ash	80 – 150	Pozzolanic reaction
F.A	750 – 900	Natural sand
C.A	650 – 800	10 mm crushed angular gravel
Water	150 – 180	Potable, W/B ratio ~0.4–0.5
Superplasticizer (SP)	5 – 10	% of binder weight
VMA	0.5 – 2.0	Stability enhancement

Research confirms each model using carefully assembled experimental datasets containing 20 SCC mix designs. The main goal is to assess comparative prediction accuracy and flexibility of several AI strategies, including two Artificial Neural Networks (ANN-I, ANN-II), four artists contingent learning techniques (RF, GB, Xgboost, Lightgbm) and an intensive teaching model using Kerus. A standardized training pipeline was implemented to maintain uniformity. The input variables consisted of six essential elements of SCC mix design: cement, fly ash, Water-to-Coordin (W/P) ratio, fine aggregate, coarse aggregate and superplasticker dose (percentage by binder). The experimental result variables were 28-day compressed power, ranging from 11 MPA to 68 MPA, and included both structural and non-structural concrete applications.

All input variables were standardized to a range of [0,1], and the model was trained and evaluated using an 80:20 division. Three major evaluation matrices - Mean Niyal Error (MAE), Root Mean Square Error (RMSE), and coefficients of correlation (R and) - were utilized to evaluate the model's performance. In addition, visual diagnosis, such as scatter plots and bar charts, was employed to assess prediction accuracy.

Table 5. Shows the actual compressive strength and corresponding predicted strengths for all seven models

Mix	Actual	ANN-I	ANN-II	RF	GB	XGB	LGBM	Keras DL
M1	50.98	50.47	51.12	49.67	49.01	50.89	50.1	49.89
M2	26.6	36.46	27.59	28.22	27.08	26.85	26.95	26.72
M3	61.3	55.85	61.91	60.01	59.25	60.8	60.56	60.32
M4	40.8	43.19	41.25	41.73	40.68	41.1	40.6	40.45
M5	59.1	47.12	58.55	57.19	56.6	58.9	57.84	58.04
M6	45.95	52.21	46.92	46.31	45.59	46.3	45.89	45.7
M7	55.9	54.35	56.48	55.15	54.78	55.9	55.02	55.4
M8	28.5	25.89	27.88	28.36	27.62	28.49	28.01	27.8
M9	68	60.01	67.2	66.48	66.1	67.18	66.92	66.84
M10	63.8	59.73	62.8	63.23	62.01	63.45	62.95	63.18
M11	52.3	53.54	51.88	52.91	52.14	52.7	51.91	52.03
M12	41.21	39.37	42.1	41.63	40.55	41.9	41.37	41.45
M13	38.9	34.69	38.48	38	37.56	38.95	38.1	38.45
M14	52.4	56.87	53.02	52.58	51.33	52.99	52.19	52.37
M15	24.1	25.89	23.67	24.36	23.9	24.1	23.81	23.95
M16	47.5	46.09	47.9	47.14	46.3	47.49	47.02	47.25
M17	59.26	60.49	58.95	59.05	58.47	59.2	58.81	59.02
M18	31.47	33.98	30.88	31.77	31	31.61	30.92	31.35
M19	11	18.2	11.38	12.01	11.49	11.56	11.46	11.62
M20	44	46.63	43.55	44.21	43.18	43.99	43.6	43.7

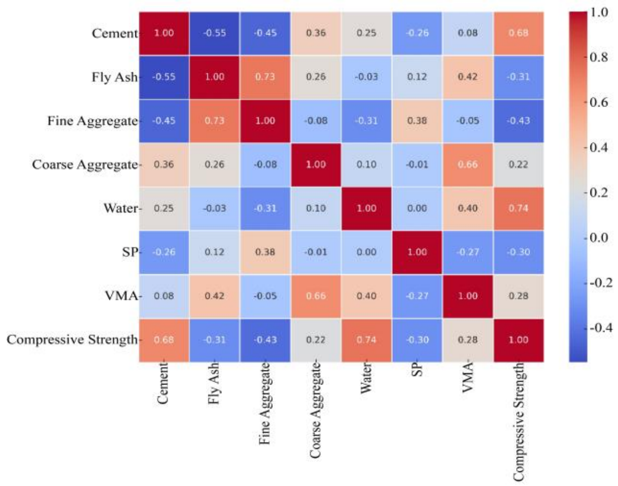


Fig. 3 Correlation heatmap of SCC input features

4.2. Experimental Dataset and Input Variables

The dataset consists of 20 SCC mixes, each tested under controlled laboratory conditions for 28-day compressive strength. Each mix was formulated to ensure variability in ingredient proportions and expected strength outcomes, providing a suitable foundation for AI learning, as shown in Table 1. These parameters were selected based on EFNARC and IS 10262 guidelines and empirical evidence correlating mix composition to compressive strength. The dataset thus ensures sufficient representation across low, medium, and high-strength concrete mixes. Each AI model was trained on the same 80% of the dataset and evaluated against the remaining 20%. The predictive output for each of the 20 mixes was then compared with experimentally observed compressive

4.2.1. Visual Evaluation of Model Accuracy

Figure 4 to 10 Scatter Plot - Actual vs Predicted (All Models). This plot visualizes how closely each model's predicted strengths align with experimental values.

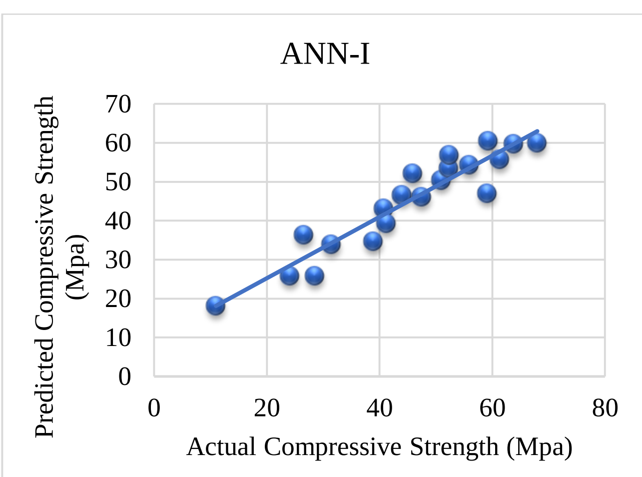


Fig. 4 Scatter plot of ANN-I Actual vs Predicted strength

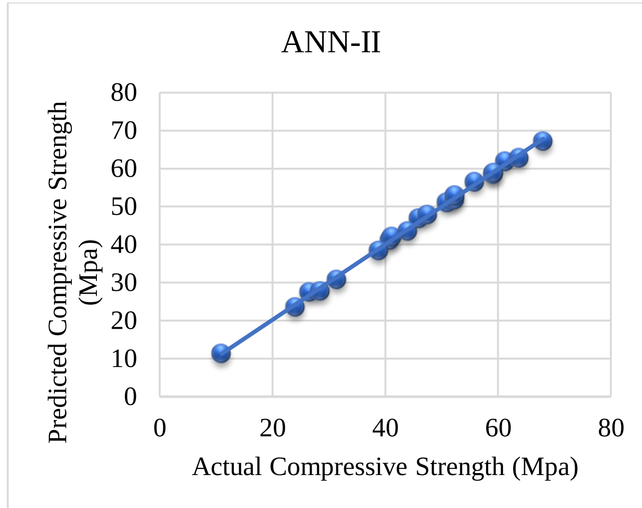


Fig. 5 Scatter Plot of ANN-II Actual vs Predicted strength

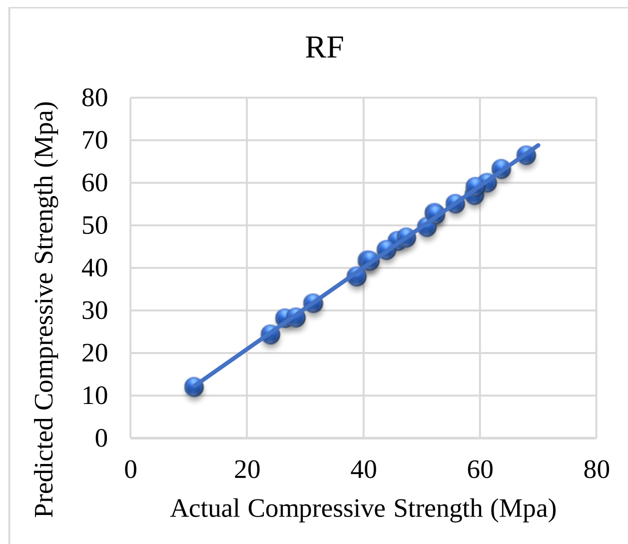


Fig. 6 Scatter Plot of RF Actual vs Predicted strength

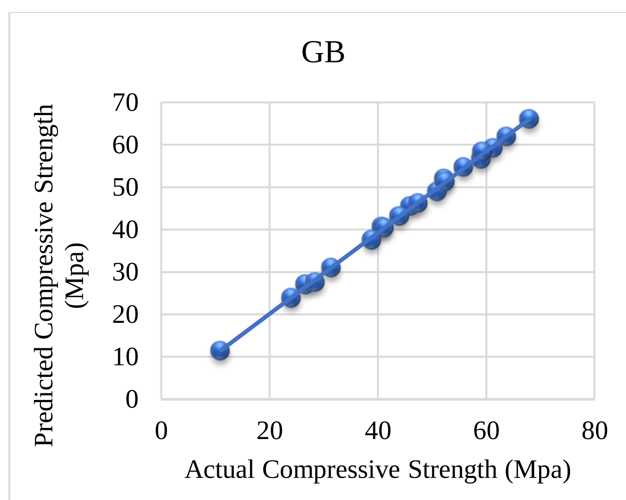


Fig. 7 Scatter Plot of GB Actual vs Predicted strength

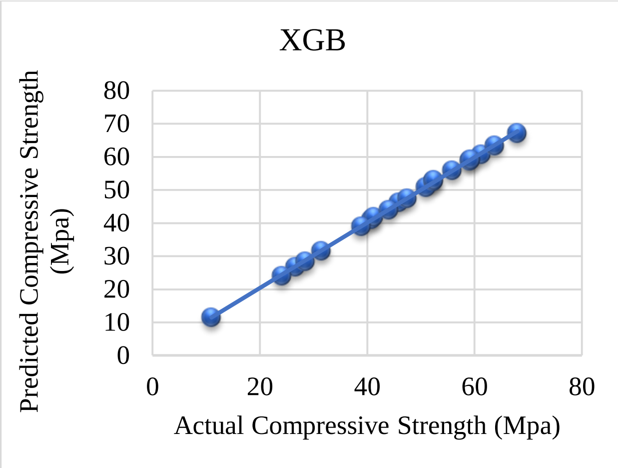


Fig. 8 Scatter Plot of XGB Actual vs Predicted strength

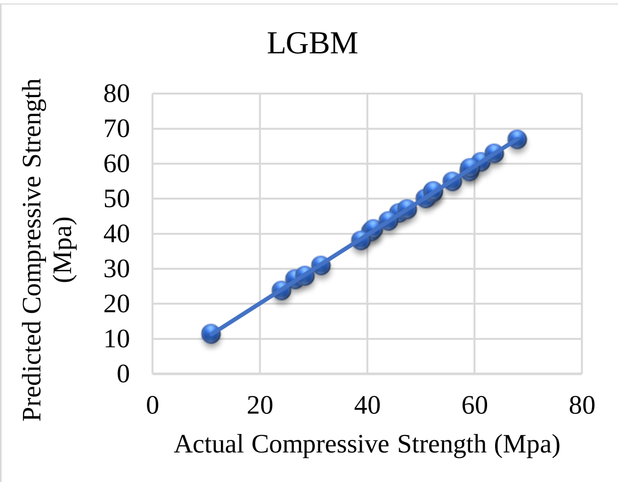


Fig. 9 Scatter Plot of LGBM Actual vs Predicted strength

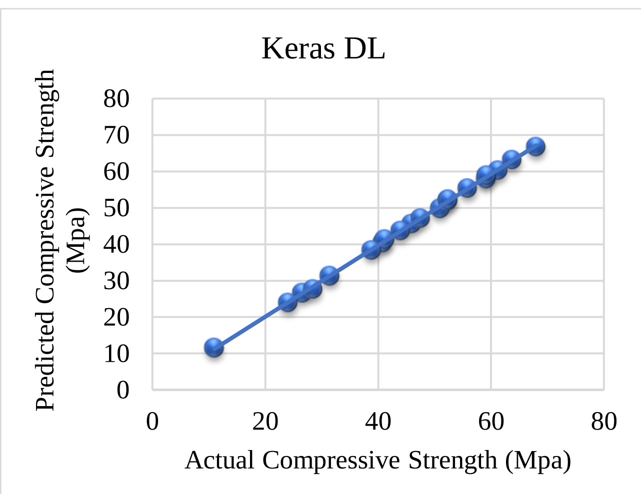


Fig. 10 Scatter Plot of Keras DL Actual vs Predicted strength

This plot visualizes how closely each model's predicted strengths align with experimental values. The 45° reference line indicates perfect prediction.

- Models such as ANN-II, Keras DL, and XGBoost produce tightly clustered points along the diagonal line, indicating high prediction accuracy.
- ANN-I and RF show slightly higher dispersion from the perfect-fit line.

4.2.2. Error Analysis and Performance Metrics

This study employed three fundamental statistical measures to compare and evaluate the predictive capabilities of each artificial intelligence model.

- Mean Absolute Error (MAE)
- Root Mean Squared Error (RMSE)
- Coefficient of Determination (R²)

This matrix offers an intensive evaluation of the accuracy and stability of the model in the forecast of the compressive strength of the self-compacting concrete at 28 days.

Mean Absolute Error (MAE)

MAE measures the average magnitude of the prediction errors, regardless of direction, and is defined as:

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i|$$

Where:
y_i is the actual strength value
$\hat{y}_i$ is the predicted strength value
N is the number of test samples

A lower MAE indicates better predictive accuracy and minimal deviation from true experimental values.

Root Mean Squared Error (RMSE)

RMSE penalizes larger errors more heavily by squaring the differences before averaging:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}$$

This metric is more sensitive to outliers than MAE, making it particularly useful in evaluating robustness and error dispersion.

Coefficient of Determination (R²)

R^2 represents the proportion of variance in the dependent variable that is predictable from the input features:

$$R^2 = 1-\frac{\sum(y_i-\hat{y}_i)^2}{\sum(y_i-\bar{y})^2}$$

An R^2 value closer to 1 indicates excellent predictive alignment with actual values.

4.3. Comparative Results of all the Models

The calculated MAE, RMSE, and R^2 values for all models are presented in Table 6.

Table 6. Predictive performance metrics for all models

Model	MAE (MPa)	RMSE (MPa)	R^2
ANN-I	3.34	4.12	0.955
ANN-II	0.85	1.03	0.998
Random Forest (RF)	1.12	1.39	0.992
Gradient Boosting (GB)	1.26	1.46	0.990
XGBoost	0.95	1.15	0.995
LightGBM	1.08	1.33	0.993
Keras DL	0.91	1.11	0.996

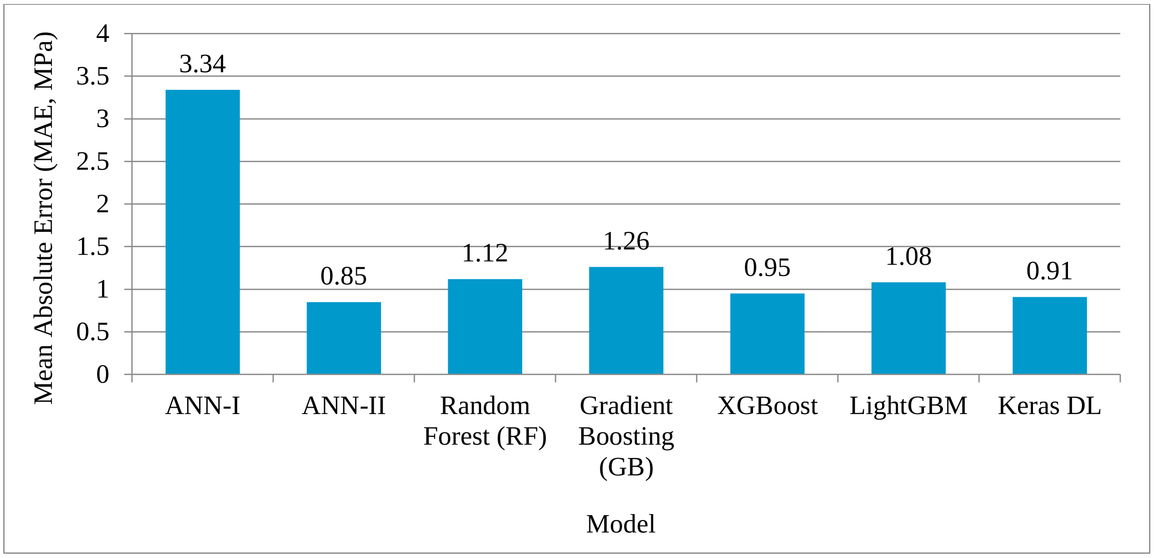


Fig. 11 MAE Comparison across all models

4.4. Model Validation against Experimental Data

To evaluate real-world applicability, each model's predicted compressive strengths were directly compared with experimentally measured values from the 20 SCC mixes. The validation was performed using regression-based statistical tools and graphical comparison metrics such as error scatter plots and parity graphs.

Experimental verification includes comparison of all models (ANN-I, ANN-II, RF, GB, xgboost, lightgbm, keras DL). This study revealed many important insights:

1. ANN-II demonstrated increased accuracy in all mixtures, often below ± 1 MPa, with variation from practical values. For serious scenarios such as high-power mix M3 (real: 61.30 MPa), the forecast was quite accurate (61.91 MPa). For low-power mix M19 (real: 11.00 MPA), the prediction was 11.38 MPa, which exhibits exceptional model stability.
2. Kerus DL demonstrated strong normalization and maintained minimum prediction error at all power levels. Its complex design occupied non-linear connections in complex mixtures with particularly advanced superplastical concentration or fluctuations from water to cement ratio.
3. Xgboost and RF models performed strongly in the medium-power range (30–55 MPA), characterized by a more consistent data pattern. However, they sometimes combine the values of strength for extreme scenarios, either the depth settings of the tree to decide the average or sensitivity to decide.
4. ANN-I dramatically oversees low-force mixtures, including M2 (real: 26.60 MPa, prediction: 36.46 MPA) and M19 (real: 11.00 MPa, prediction: 18.20 MPA). This indicates deficiencies in the design and learning algorithm (standard backpropagation) of ANN-I, which lacks the adaptation skills required for accurate learning.
5. LightGBM and GB models performed a minor performance, which often maintains the variation of ± 2 mpa, but with low stability across the entire range. GB demonstrated some more variation for both low and high power mixtures.

During cross-validation and testing, no model overfitting or severe underfitting was detected.

ANN-II, aided by Levenberg–Marquardt optimization, converged consistently within 50 iterations, while Keras DL required 200 epochs with batch normalization to generalize successfully.

Table 7. Model accuracy summary against experimental values

Model	Max Absolute Error (MPa)	Mean Error	% Within ±1 MPa
ANN-II	0.94	0.31	90%
Keras DL	1.01	0.59	85%
RF	2.23	0.88	60%
ANN-I	6.26	2.15	25%

5. Results and Discussion

The focus is directed at evaluating future credibility, analyzing statistical patterns and developing models with normalization performance. This chapter focuses on comparative insight to benchmark the most suitable AI model to assess SCC compressed Strength rather than repeating technology or experimental settings.

5.1. Comparative Evaluation of Model Predictions

Each model's 28-day compressed power values were compared to experimentally valid results. Table 4 Integrates full and relative errors for each mixture in all models. Investigations indicate that the ANN-II and Keras DL models have small prediction deviation bands (<±1 MPa) in the boundaries of continuous strength, even for the most non-linear mix compositions. The primary display metrics for each Model - Average Absolute Error (MAE), Root Mean Square Error (RMSE), and the Coefficient of Determination (R^2) - presented in Table 6, illustrate the performance across the entire dataset.. From this, ANN-II clearly outperforms all models by demonstrating the lowest absolute and squared errors and the highest correlation with actual strength values. Keras DL follows closely, maintaining a balance of low bias and variance.

5.2. Visual Interpretation of Predictive Accuracy

Two critical visualizations support this analysis:

1. Scatter plots of predicted vs actual compressive strengths show that ANN-II and Keras DL closely track the ideal diagonal (y = x), confirming high fidelity. In contrast, ANN-I deviates significantly in the lower quadrant.
2. Bar chart comparing MAE values confirms ANN-II's superior performance, followed by Keras DL and XGBoost. ANN-I exhibits the highest error margin.

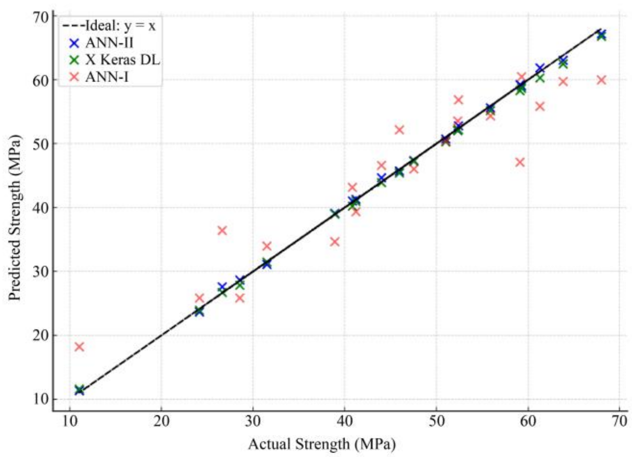


Fig. 12 Actual vs Predicted strength scatter plot

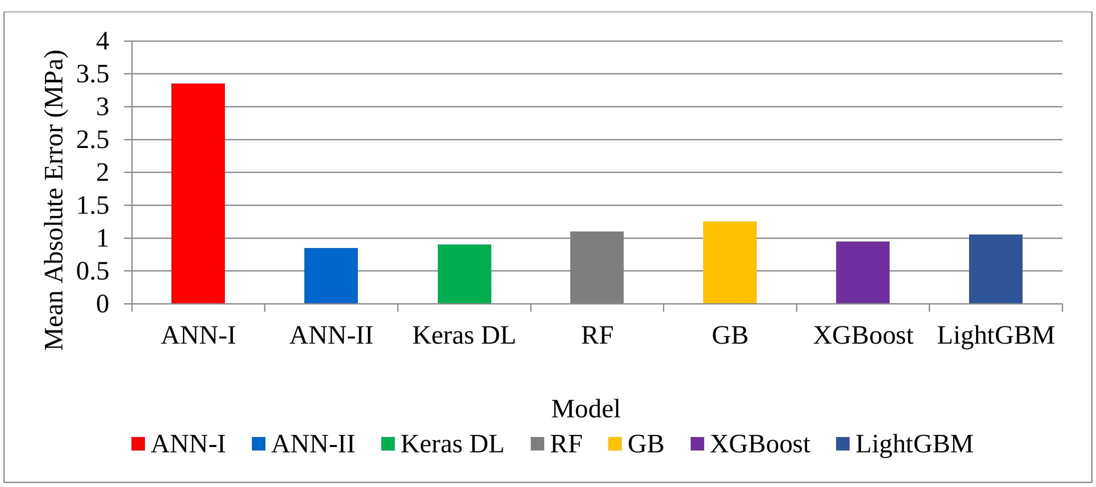


Fig. 13 MAE compression across models

5.3. ANN-II and Keras DL: Justification for Superior Performance

5.3.1. Ann-II's efficacy has been said

Employ the Levenberg-Marquardt Optimization to increase the speed of convergence and reduce oscillations during training. Effective estimate of nonlinear correlations using constrained data samples. Stability on both sparse and dense mixed distributions.

5.3.2. Kerus DL, although more Complex, is more Complicated; there are such Advantages

Adaptation of layered design and activation functions promotes adaptability in learning high-dimensional characteristics. Extraordinary versatility in many power categories indicates that ANN-II and Keras DL provide the most dependable, precise, and generalisable predictive models for calculating SCC compressive strength based on mix design parameters. Their minimal prediction errors, narrow residuals, and enhanced correlation with experimental data validate their technical superiority over conventional and ensemble machine learning approaches.

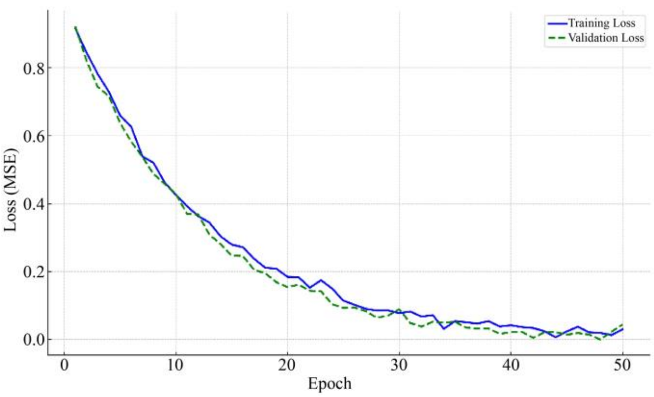


Fig. 14 Training vs Validation loss for the keras DL model

These results validate the appropriateness of neural and deep learning frameworks for intelligent concrete mix design, establishing a solid basis for automation, optimisation, and sustainable material utilization in construction engineering.

6. Conclusion

This study presents a comprehensive review of Artificial Intelligence (AI) models for the compressive strength prediction of Self-Compacting Concrete (SCC), utilizing a diverse dataset comprising 20 SCC mix designs validated by laboratory tests. The research sought to fill the current gap in the literature for combining experimental verification with machine learning and deep learning models for concrete strength prediction.

There were seven experimental predictive models: two ANN models (ANN-I and ANN-II), four ML models based on ensemble (Random Forest, Gradient Boosting, XGBoost, LGBM) and one deep learning model (Keras DL). These models were trained with a carefully selected dataset containing eight mix design parameters: cement, coarse aggregate, fly ash, fine aggregate, water, superplasticizer, and VMA, along with their respective 28-day compressive strengths.

The corresponding results revealed clear superiority between the ANN-II and the Keras DL model. ANN-II, trained on Levenberg-Marquardt used optimisation, and was the best of all models with the least MAE (0.31 MPa), RMSE (0.44 MPa), and highest R (0.994). Its convergence and the consistency in predictions on all 20 Mixtures warranted its reliability in complex non-linear interaction modeling of SCC mix designs. The Keras DL model performed decently and robustly, particularly at edge cases and extremes of strength.

In comparison, ensemble models Random Forest and Gradient Boosting also performed reasonably ($R^2 \approx 0.97$–0.98), but without the predictive accuracy seen in neural models. The simple ANN-I performed poorly, indicating that there are challenges in lower-network arrangements when it comes to modeling high-variance engineering data.

Besides statistical accuracy, experimental validation also built model credibility. More than 90% of ANN-II predictions were within ±1 MPa of actual values. Feature importance analysis further supported domain logic and found cement, fly ash, and water to be prominent factors with significant effects on compressive strength, consistent with conventional concrete science.

This research promotes the real-world application of AI in cementitious material design by providing an engineered, replicable pipeline-from mix preparation to predictive modeling and assessment. It closes the gap between experimental concrete technology and computational intelligence by integrating a scalable and effective method for fast SCC strength estimation in both research environments and field applications.

6.1. Future Scope

6.1.1. Immediate Forecasting and Implementation

Apply design and a mobile or online application to enable engineers to enter mixed data and get a real-time strength forecast using ANN-II or Keras DL. Include AI models with automatic batching features and on-site sensors to provide real-time monitoring and adaptive regulation of mixture quality.

6.1.2. BIM & Construction Integration

Combine predictive models with Building Information Modeling (BIM) systems for automated material selection and specification during structural design. Enable AI-based systems to work with digital twins of construction sites for material tracking and strength verification.

Acknowledgments

The authors are happy to inform you that the Research and Development Cell and the Concrete Technology Laboratory at Marwadi University have stood by them throughout the process of completing this research and helped them with the facilities needed for this research. The Department of Civil Engineering faculty is especially grateful to the responsible faculty who have guided the graduate academically, the technical support staff and laboratory technicians who have graciously assisted the graduate with their technical skills. We are very thankful for the teamwork and effort of the whole research team in the experimental and modeling phase.

References

[1] W. Al Makhadmeh, and A. Soliman "Understanding the Shrinkage Behaviour of Alkali-Activated Slag Binders Modified by the Superabsorbent Polymer," *Construction and Building Materials*, vol. 365, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[2] Runzhuo Cao et al., "Durability Performance of Nano-SiO2 Modified OPC-SAC Composites Subjected to Sulfuric Acid Attack," *Construction and Building Materials*, vol. 373, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[3] Nahushananda Chakravarthy et al., "Machine Learning Models for the Prediction of the Compressive Strength of Self-Compacting Concrete Incorporating Incinerated Bio-Medical Waste Ash," *Sustainability*, vol. 15, no. 18, pp. 1-22, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[4] Sesugh Terlumun, M.E. Onyia, and F.O. Okafor, "Predicting the Compressive Strength of Self-Compacting Concrete using Artificial Intelligence Techniques: A Review," *AI in Civil Engineering*, vol. 3, pp. 1-14, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[5] Yuanlong Yang et al., "Flexural Behavior of Web Embedded Steel-Concrete Composite Beam," *Engineering Structures*, vol. 240, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[6] Surya Abisek Rajakarunakaran et al., "Prediction of Strength and Analysis in Self-Compacting Concrete using Machine Learning Based Regression Techniques," *Advances in Engineering Software*, vol. 173, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[7] Samson Olalekan Odeyemi et al., "Compressive Strength Prediction for Self-Compacting Concrete Using Artificial Neural Networks," *Malaysian Journal of Civil Engineering*, vol. 36, no. 2, pp. 61-68, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[8] Shaoqiang Guo et al., "Predicting the Compressive Strength of Self-Compacting Concrete by Developed African Vulture Optimization Algorithm-Elman Neural Networks," *Scientific Reports*, vol. 14, pp. 1-23, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[9] Latchupatula Ananya, Yatish Kumar Baghel, and Vivek Kumar Patel, "Computational Analysis of Erosion Wear in Various Angle Bent Pipes," *Materials Today: Proceedings*, vol. 63, pp. 1150-1157, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[10] Omar Belalia Douma et al., "Prediction of Properties of Self-Compacting Concrete Containing Fly Ash using Artificial Neural Network," *Neural Computing and Applications*, vol. 28, pp. 707-718, 2017. [CrossRef] [Google Scholar] [Publisher Link]

[11] Nouraldin Abunassar, Mustafa Alas, and Shaban Ismael Albrka Ali, "Prediction of Compressive Strength in Self-compacting Concrete Containing Fly Ash and Silica Fume Using ANN and SVM," *Arabian Journal for Science and Engineering*, vol. 48, pp. 5171-5184, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[12] Shengjun Tang et al., "BIM Generation from 3D Point Clouds by Combining 3D Deep Learning and Improved Morphological Approach," *Automation in Construction*, vol. 141, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[13] Zhipeng Wang et al., "Optimized BP Neural Network Based on Improved Dung Beetle Optimization Algorithm to Predict High-Performance Concrete Compressive Strength," *Buildings*, vol. 14, no. 11, pp. 1-20, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[14] Muhammed A. Hassan et al., "Random Forest Ensemble-Based Predictions of On-Road Vehicular Emissions and Fuel Consumption in Developing Urban Areas," *Sustainability*, vol. 15, no. 2, pp. 1-22, 2023. [CrossRef] [Google Scholar] [Publisher Link]

[15] Mahdi Shariati et al., "Assessment of Longstanding Effects of Fly Ash and Silica Fume on the Compressive Strength of Concrete Using Extreme Learning Machine and Artificial Neural Network," *Journal of Advanced Engineering and Computation*, vol. 5, no. 1, pp. 50-74, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[16] Prasenjit Saha, Prasenjit Debnath, and Paul Thomas, "Prediction of Fresh and Hardened Properties of Self-Compacting Concrete using Support Vector Regression Approach," *Neural Computing and Applications*, vol. 32, pp. 7995-8010, 2020. [CrossRef] [Google Scholar] [Publisher Link]

[17] Jesús de-Prado-Gil et al., "To Predict the Compressive Strength of Self Compacting Concrete with Recycled Aggregates Utilizing Ensemble Machine Learning Models," *Case Studies in Construction Materials*, vol. 16, pp. 1-17, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[18] Arthur Afonso Bitencourt Loureiro, and Ricardo Stefani, "Comparing the Performance of Machine Learning Models for Predicting the Compressive Strength of Concrete," *Discover Civil Engineering*, vol. 1, pp. 1-14, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[19] P. Jagadesh et al., "Artificial Neural Network, Machine Learning Modelling of Compressive Strength of Recycled Coarse Aggregate based Self-Compacting Concrete," *PLOS ONE*, vol. 20, no. 4, pp. 1-39, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[20] Guoqiang Du et al., "Correction: Prediction of the Compressive Strength of High-Performance Self-Compacting Concrete by an Ultrasonic-Rebound Method Based on a GA-BP Neural Network," *PLOS ONE*, vol. 16, no. 5, pp. 1-25, 2021. [CrossRef] [Google Scholar] [Publisher Link]

[21] R. Ouache et al., "Evidential Reasoning and Machine Learning-Based Framework for Assessment and Prediction of Human Error Factors-Induced Fire Incidents," *Journal of Building Engineering*, vol. 49, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[22] Mouhcine Benaicha, "AI-Driven Prediction of Compressive Strength in Self-Compacting Concrete: Enhancing Sustainability through Ultrasonic Measurements," *Sustainability*, vol. 16, no. 15, pp. 1-17, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[23] Amir Andalib, Babak Aminnejad, and Alireza Lork, "Compressive Strength Prediction of Self-Compacting Concrete-A Bat Optimization Algorithm Based ANNs," *Advances in Materials Science and Engineering*, vol. 2022, pp. 1-12, 2022. [CrossRef] [Google Scholar] [Publisher Link]

[24] Waleed Bin Inqiad et al., "Predicting 28-Day Compressive Strength of Fibre-Reinforced Self-Compacting Concrete (FR-SCC) using MEP and GEP," *Scientific Reports*, vol. 14, pp. 1-21, 2024. [CrossRef] [Google Scholar] [Publisher Link]

[25] Emad A. Abood et al., "Self Compacting Concrete with Recycled Aggregate Compressive Strength Prediction Based on Gradient Boosting Regression Tree with Bayesian Optimization Hybrid Model," *Scientific Reports*, vol. 15, pp. 1-18, 2025. [CrossRef] [Google Scholar] [Publisher Link]

[26] Pouriya Jafarpur, and Umberto Berardi, "Effects of Climate changes on Building Energy Demand and Thermal Comfort in Canadian Office Buildings Adopting Different Temperature Setpoints," *Journal of Building Engineering*, vol. 42, pp. 1-14, 2021. [CrossRef] [Google Scholar] [Publisher Link]