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Experimental Investigation and Machine Learning-Based Prediction of the Mechanical and Durability Performance of Nano-Modified Fiber-Reinforced Concrete

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Abstract

With the growing demand for high performance and durable concrete, advanced cementitious composites with nanomaterials and fiber reinforcement have been developed. Nano-modified fiber reinforced concrete can improve matrix densification, crack resistance, mechanical performance and durability through complementary mechanisms at different scales but its performance is dependent on complex interactions among binder composition, water to binder ratio, nanomaterial dosage, fiber content, admixture dosage, aggregate characteristics and curing age so conventional trial-and-error mix design is time consuming and resource intensive. In this paper an integrated experimental and AI based machine learning framework is proposed to investigate and predict the mechanical and durability performance of nano-modified fiber reinforced concrete. Nano silica is considered as the main nanomodifying material while fiber reinforcement is incorporated in controlled proportions to study its interaction with nano scale matrix modification. An experimental program is proposed to evaluate fresh properties, compressive strength, split tensile strength, flexural strength, water absorption, sorptivity and some durability characteristics at different curing ages. The experimentally generated dataset will then be used to train and compare machine learning models (artificial neural networks, random forest regression, support vector regression, gradient boosting and extreme gradient boosting), statistical indicators (coefficient of determination R^2 , root mean square error RMSE, mean absolute error MAE and mean absolute percentage error MAPE) will be used to evaluate model performance and explainable artificial intelligence techniques will be applied to find out the relative contribution of mixture parameters to the predicted concrete performance. The framework proposed here establishes a reliable relationship between concrete composition and performance without requiring extensive experimental trial-and-error procedures. Laboratory experimentation, machine learning prediction, feature importance analysis and data driven optimization are expected to provide practical methodology for developing high performance nano-modified fiber reinforced concrete and more efficient sustainable concrete mix design.

Keywords: Nano-silica; Fibre reinforced concrete; Nano modified concrete; Artificial intelligence; Machine learning; Concrete strength prediction; Durability; Explainable AI; Sustainable concrete; Mix design optimization.

1. Introduction

Concrete is one of the most widely used construction materials because it is available, versatile, relatively cheap and can satisfy different structural requirements. However, conventional concrete has heterogeneous microstructure, low tensile strength, cracking and deterioration under mechanical and environmental actions. Its performance depends on several interacting factors (cement content, water-to-binder ratio, aggregate characteristics, admixtures, curing conditions and age), so trial-and-error mix design can be a very time consuming process to obtain an optimum balance between strength, workability, durability and crack resistance.

Nanotechnology offers an effective approach for improvement in microstructure and performance of cement-based materials. Among various nanomaterials nano-silica is particularly promising because of its high surface area, pozzolanic activity and ability to promote hydration and refine pore structure. When properly dispersed nano-silica improves strength and reduces permeability but excessive dosage or poor dispersion increases water demand, causes agglomeration and reduces workability. Thus selection of right nano-silica dosage is important for optimum concrete performance.

Fiber reinforcement is another way to improve concrete performance (crack control, tensile resistance, flexural strength and toughness). Fibers like polypropylene and steel can restrict crack propagation and post-cracking behavior but excessive fiber content may reduce workability and cause mixing problems. Nano-silica with fibers can provide a multiscale reinforcement mechanism where nano-silica modifies the cementitious matrix and fibers control cracks at larger scales but overall performance depends on interaction among nano-silica dosage, fiber content, binder composition, water content, admixtures and curing age.

The increasing number of interacting mixture parameters also makes empirical prediction models difficult. Artificial intelligence (AI) and machine learning (ML) offer an alternative data driven approach to identify complex nonlinear relationships between constituents and performance. Models such as artificial neural networks, random forest, support vector regression, gradient boosting and XGBoost can be used to predict mechanical and durability properties from parameters such as cement content, w/b ratio, aggregate quantities, nano-silica dosage, fibre content, admixture dosage and curing age. However, ML prediction can only be reliable if enough data is available, preprocessing is done properly, suitable feature selection is applied, cross-validation is used, independent testing is performed and data leakage is avoided.

Model interpretability is also necessary for practical engineering applications. Accuracy of a prediction alone does not tell why a model gives a particular result or which mixture parameters have the biggest influence. Feature-importance methods and XAI (explainable artificial intelligence) can then be used to evaluate relative contribution of nano-silica, fiber dosage, curing age, water-to-binder ratio and other variables; such analysis establishes meaningful connection between ML predictions and concrete-material mechanisms known from experiments. Experimental investigation with ML therefore can provide physical evidence as well as computational insight for predicting concrete properties and mixture proportions. Although much work has been carried out on nano-modified concrete, fiber reinforced concrete and ML based concrete prediction but relatively little work has been systematically integrated among these three areas using common experimental dataset.

Thus, in this study an integrated experimental and ML framework is proposed for investigating mechanical and durability performance of nano-modified fibre reinforced concrete. Nano silica is selected for matrix densification while fibre reinforcement is used for crack control. Different nano-silica and fiber dosages will be experimentally tested; ML modelling (ANN, RF, SVR, Gradient Boosting and XGBoost) comparison will be done; R^2 , RMSE, MAE and MAPE models performance will be evaluated; XAI techniques will identify influential mixture variables. The proposed framework should help in efficient mix optimisation and reduce reliance on extensive trial and error experimentation.

2. Literature Review

2.1 Nanomaterials in Concrete

Nanomaterials have attracted a lot of attention in cement-based materials because their extremely small particle size and high specific surface area allow them to modify concrete at micro and nano scale; nano-silica, nano-alumina, nano-titania, carbon nanotubes, graphene based materials and nanoclay have been studied for improving concrete properties (e.g., filler effect, nucleation ability, pozzolanic reactivity etc.) but nano-silica is particularly attractive due to its filler effect, nucleation ability and pozzolanic reactivity which can affect hydration, pore structure, strength permeability and durability. Performance of nanoparticles depends on particle characteristics, dosage, dispersion, water/binder ratio, curing and compatibility with chemical admixtures. Poor dispersion leads to agglomeration and reduces effectiveness of nanoparticles so incorporation of nanomaterials should be considered as multi-variable process requiring appropriate dosage and mixing procedures.

2.2 Nano-Silica modified concrete

Nano-silica is one of the most widely studied nanomaterials for improvement of cementitious composites. Its high surface area and reactive silica content promote pozzolanic reactions with calcium hydroxide and add to C-S-H formation. Fine particles can also fill small voids and refine pore structure so that the matrix density is

increased and mechanical and durability performance could be improved. Generally beneficial effects were found at optimized nano-silica contents (2–4% was often cited as an effective range), although optimum dosage depends on mixture composition and processing conditions. Increasing nano-silica will increase water demand and reduce workability because of its high surface area so the performance of nano-silica concrete should not be evaluated by strength alone but rather strength, durability, workability and microstructural characteristics together.

2.3 Mechanical Performance of Nano-Modified Concrete

The mechanical performance of nano-modified concrete is strongly controlled by hydration enhancement, additional C-S-H formation, pore refinement and bonding within cementitious matrix. Nano-silica can improve compressive strength by producing a denser and more refined microstructure; tensile and flexural properties can be affected by improving cement paste–aggregate interface and modifying crack initiation characteristics. However, improvements in tensile and flexural strength do not necessarily translate to compressive-strength enhancement since cracking and reinforcement mechanisms are strong functions of these properties. The literature therefore shows that the response to nano-silica is multi-dimensional (an optimum dosage for compressive strength may not give best combination of tensile strength, flexural performance, workability and durability), so multiresponse evaluation is important in advanced concrete mix design.

2.4 Durability of Nano-modified Concrete

Concrete durability is closely related to pore structure and resistance to penetration of water and aggressive substances. Important durability indicators are water absorption, permeability, chloride ingress, carbonation, sulfate attack and chemical deterioration. Nano-silica reduces pore connectivity and increases matrix density by pore refinement and secondary hydration (see above). These changes reduce movement of aggressive substances through concrete and thus improve service life. However, durability performance depends on curing conditions, dispersion quality, mixture composition and nano-silica dosage. Poor dispersion can lead to agglomerated regions while excessive nano-silica increases water demand and nonuniformity. So durability improvement should be verified experimentally not only from nano-silica incorporation.

2.5 Fiber-Reinforced Concrete

Fibers are used as an alternative to nanomaterials because cracking control and stress transfer across developing cracks are achieved by fibers too (unlike nanomaterials which modify the cementitious matrix). At a larger structural scale, fibers can improve tensile resistance, flexural performance, toughness and post-cracking behaviour. Steel fibers generally have good crackbridging and post-cracking capacity whereas synthetic fibers (e.g polypropylene) are usually used for microcrack and shrinkage-crack control. The effectiveness of fibers depends on type, dosage, length, diameter, aspect ratio, orientation, dispersion and bond with surrounding matrix. Excess fiber content reduces workability and causes nonuniform distribution so proper type and dosage of fiber is needed to achieve balance between mechanical performance, crack control and fresh state workability.

2.6 Nano-Modified Fiber Reinforced Concrete

The combination of nano-silica and fiber reinforcement provides multi-scale approach to concrete performance enhancement. Nano-silica can refine the cement paste and interfacial transition zone while fibers bridge cracks and improve post-cracking behaviour. Dense matrix produced by nano-silica may also enhance bond between fibers and surrounding cement paste (possibly complementary effects). However, combined system adds complexity because both nano-silica and fibers increase viscosity, water demand and workability. Poor flowability leads to poor compaction and nonuniform fiber distribution which offsets expected improvement in hardened properties. Although individual benefits of nanomaterials and fibres are known, their combined effect requires further systematic experimental study and this is basis for developing an integrated experimental and machine learning framework for nano modified fibre reinforced concrete.

3. Methodology

3.1 Research Design

The present study adopts an integrated experimental and artificial intelligence (AI)-based machine learning (ML) methodology to investigate the mechanical and durability performance of nano-modified fiber-reinforced concrete. The research is designed in two interconnected phases. The first phase involves laboratory preparation and characterization of concrete incorporating nano-silica and fiber reinforcement. The second phase uses the experimentally generated dataset to develop, train, validate, and interpret machine learning models for predicting concrete performance.

The overall research methodology consists of the following stages:

Material selection → Material characterization → Mix proportioning → Specimen preparation → Curing → Experimental testing → Dataset generation → Data preprocessing → ML model development → Model evaluation → Explainable AI → Mix optimization → Experimental validation

The experimental program will establish the relationship between the proportions of constituent materials and the resulting properties of concrete. The machine learning component will subsequently identify nonlinear relationships within the experimental data and provide predictions for selected mechanical and durability properties.

3.2 Materials

The present study uses experimental and AI-ML (machine learning) methodology to study mechanical and durability performance of nano-modified fiber reinforced concrete. The work is planned in two phases connected to each other: the first phase is laboratory preparation and characterization of concrete containing nano-silica and fibre reinforcement; second phase uses the experimentally generated dataset to develop, train, validate and interpret machine learning models for predicting concrete performance. In general the research methodology is as follows:

Material selection → Material characterisation → Mix proportioning → Specimen preparation → Curing → Experimental testing → Dataset generation → Data preprocessing → ML model development → Model evaluation → Explainable AI → Mix optimisation → Experimental validation.

The experimental program will establish the relation between the proportions of constituent materials and properties of concrete. Machine learning part will then identify nonlinear relationships in the experimental data and make predictions for selected mechanical and durability properties.

3.2.1 Cement

Ordinary Portland Cement conforming to the relevant Indian Standard applicable shall be used as primary binder. The cement will be characterized for standard consistency, initial and final setting times, soundness, specific gravity and fineness. Chemical and physical properties will be recorded before concrete preparation.

3.2.2 Fine Aggregate

Natural river sand or manufactured sand suitable for concrete production will be used as fine aggregate. Particle-size distribution, specific gravity, water absorption, bulk density and fineness modulus will be determined; grading should comply with requirements for concrete aggregates.

3.2.3 Coarse Aggregate

Crushed coarse aggregate of nominal maximum size suitable will be used. Specific gravity, water absorption, aggregate impact/crushing characteristics and gradation will be determined before mix preparation. Same source of aggregate should preferably be used throughout the experimental program to avoid uncontrolled variability.

3.2.4 Nano-Silica

Commercial nano-silica will be selected as the principal nanomaterial. Its particle size, specific surface area, silica content, physical form and manufacturer specifications will be recorded. Nano-silica will be incorporated as partial replacement of cement by mass. As nanoparticles have a strong tendency to agglomerate special attention will be paid to dispersion. Nano-silica will be dispersed by appropriate mixing procedure (water and/or compatible high range water reducing admixture may also be used).

3.2.5 Fiber

A suitable fiber (preferably polypropylene fibre or steel fibre) will be selected from the laboratory based on availability. Length, diameter, density, aspect ratio, tensile strength and manufacturer specifications will be recorded. For a practical first experimental program polypropylene fibre can be chosen because it is available and relatively easy to incorporate into conventional concrete. If structural toughness and post cracking behaviour are of interest then steel fibre might contribute more in mechanical research.

3.2.6 Chemical Admixture

High range water reducing admixture/superplasticizer compatible with cement selected and nano silica will be added where necessary to maintain workability desired. Dosage will be carefully controlled as changes in admixture content affect fresh and hardened concrete properties.

3.3 Experimental Mix Design.

Control concrete mixture without nano-silica and fiber will first be made. Nano-silica and fiber will then be introduced at selected dosage levels.

Table1: A preliminary experimental matrix is proposed below

Mix ID	Nano-silica (% binder)	Fiber (% by volume)	Description
M0	0	0	Control concrete
M1	1	0	Nano-modified
M2	2	0	Nano-modified
M3	3	0	Nano-modified
M4	0	0.25	Fiber-reinforced
M5	1	0.25	Nano + fiber

M6	2	0.25	Nano + fiber
M7	3	0.25	Nano + fiber
M8	1	0.50	Nano + higher fiber
M9	2	0.50	Nano + higher fiber
M10	3	0.50	Nano + higher fiber

These percentages are proposed starting levels, not final values. The final dosage range should be established based on the selected concrete grade, material properties, workability, laboratory resources, and preliminary trials.

The control mixture is essential because it provides a reference against which the individual and combined effects of nano-silica and fiber can be evaluated.

3.4 Preparation of Nano-Silica Dispersion:

nano-silica will be incorporated carefully so as to avoid particle agglomeration. The amount of nano-silica required will first be measured according to the replacement level given above. The nano-silica will then be added to a portion of the mixing water and dispersed mechanically (by stirring) or by other dispersion technique (e.g., bubble dispersion). Superplasticizer may be added to the dispersion where required. The dispersion procedure should be the same for all nano-silica mixtures since energy of dispersion or mixing time may vary and affect the performance of nanomaterial.

3.5 Concrete mixing procedure

Concrete will be mixed in a laboratory mechanical mixer. The general sequence will be:

- 1) Coarse aggregate and fine aggregate will be put into the mixer.
- 2) Cement will be added and dry-mixed with aggregates.
- 3) The prepared nano-silica dispersion will be introduced gradually.
- 4) A small amount of mixing water will be added.
- 5) Superplasticizer will be added according to the dosage specified.
- 6) Fiber will be introduced slowly to avoid balling and uniform dispersion.
- 7) Mixing will continue until a homogeneous mixture appears visually.
- 8) Fresh concrete will be tested immediately for workability.

Concrete specimens will then be cast into properly prepared moulds. The same mixing sequence and mixing time should be used for all mixtures.

3.6 Fresh Concrete Testing

3.6.1 Workability

The workability of each concrete mixture will be determined using the appropriate slump test or another suitable workability test depending on concrete consistency. Effect of nano-silica and fiber on workability will be studied because both materials can affect rheological behaviour of concrete. Measured workability will also be included as a potential ML input variable in dataset.

3.6.2 Density

Fresh concrete density will be measured where required. This parameter can provide an additional indicator of mixture uniformity and can later be evaluated as a ML input.

3.7 Specimen Preparation and Curing

Concrete specimens will be prepared for compressive, tensile, flexural and durability testing according to applicable standards. After casting specimens will be compacted well and stored under controlled conditions. After demoulding specimens will be transferred to curing environment maintained at approximately standard laboratory curing conditions. Testing will be done at selected ages (preferably 7, 28 and 56 days) The 28-day age will be the main reference age and 7- and 56-day testing will give information on early-age and later-age performance.

3.8 Mechanical Properties

3.8.1 Compressive Strength

Compressive strength will be measured according to standard concrete compression tests. At least three replicate specimens should preferably be tested for each mixture and curing age. The average compressive strength will be calculated and the variability among replicate specimens recorded. This will be one of the principal target variables for the ML models.

3.8.2 Split Tensile Strength

The split tensile strength of cylindrical concrete specimens will be determined at selected curing ages. Fiber reinforcement is expected to affect tensile behaviour through crack bridging while nano-silica may influence matrix and interfacial transition zone. Experimental tensile strength will be used as a second ML target variable.

3.8.3 Flexural Strength

Flexural strength will be measured using beam specimens loaded by standard flexural loading procedure. Particular attention will be paid to the effect of fiber dosage since fiber reinforcement is expected to affect crack development and post cracking response.

3.9 Durability Testing

The durability component can be expanded according to laboratory facilities available.

3.9.1 Water Absorption

Water absorption will be measured to determine how much water the concrete can absorb through its pore system (lower water absorption usually means denser less permeable matrix).

3.9.2 Sorptivity. Sorptivity testing will be performed to measure rate of capillary water uptake

3.9.3 Chloride Resistance

If suitable laboratory facilities are available chloride-ion penetration or equivalent chloride transport test can be included. This will provide a stronger durability component for the study.

3.9.4 Sulfate/Acid

Exposure Some mixtures may also be exposed to sulfate or acidic environment. Changes in mass, compressive strength, surface condition etc. can be recorded. For a manageable first study water absorption + sorptivity + compressive strength would give practical minimum durability component.

3.10 Experimental Dataset Development

We will convert experimental results into structured dataset for machine learning.

Table 2: Shows the Potential input variables include

Variable	Type	Unit	Proposed Value / Range
Cement content	Numerical	kg/m ³	400–500
Water content	Numerical	kg/m ³	150–180
Fine aggregate	Numerical	kg/m ³	650–800
Coarse aggregate	Numerical	kg/m ³	900–1100
Water/binder ratio	Numerical	–	0.30–0.40
Nano-silica content	Numerical	%	0–3
Fiber content	Numerical	%	0–0.50
Superplasticizer content	Numerical	%	0.5–1.5
Curing age	Numerical	days	7, 28, 56
Workability	Numerical	mm	55–95

Compressive strength

- 1) Split tensile strength
- 2) Flexural strength
- 3) Water absorption
- 4) Sorptivity
- 5) Durability indicator

Each row of the dataset should represent an individual experimental observation rather than merely one mix designation.

Replicate observations should be retained where statistically appropriate, while average values can also be considered depending on the modelling strategy.

3.11 Data Preprocessing

The experimental dataset will be preprocessed before ML model development. The following steps will be considered:

- 1) Identification of missing observations.
- 2) Identification of obvious measurement errors.
- 3) Detection of extreme outliers.
- 4) Examination of variable distributions.
- 5) Correlation analysis.
- 6) Feature scaling where required.
- 7) Encoding of categorical variables, if any.
- 8) Training/testing data separation.

A key principle will be that information from the final test dataset must not be used in model training or hyperparameter optimization (data leakage) and that this gives a more realistic estimate of model generalization.

3.12 Machine learning models

Several machine-learning algorithms will be considered rather than one single model:

3.12.1 Artificial Neural Network

An ANN model will be developed to represent nonlinear relationships between mixture parameters and concrete properties. The model will have an input layer, one or more hidden layers and an output layer. The number of neurons and hidden layers will be determined systematically by tuning the model not arbitrarily.

3.12.2 Random Forest

Regression Random Forest is chosen because ensemble tree models can capture nonlinear relationships and interactions among variables as well as useful feature-importance information.

3.12.3 Support Vector Regression

SVR will be considered because it can provide effective nonlinear regression performance (especially for datasets with relatively few observations).

3.12.4 Gradient Boosting

Gradient Boosting will be considered as an ensemble-learning approach in which sequential models are developed to reduce prediction errors.

3.12.5 XGBoost

XGBoost will be considered because it models nonlinear interactions and is widely used in engineering prediction problems; the algorithms will be compared using the same dataset and validation strategy. 3.13 Training and Validation Strategy. The experimental dataset available will be split into training and testing subsets (if enough observations are available) e.g.: 70% training + 15% validation + 15% testing. k-fold cross-validation can be used if the experimental dataset is relatively small to obtain a more robust estimate of model performance. The final test data will not depend on any model training or hyperparameter tuning.

3.14 Model Performance Evaluation

The developed models will be evaluated using several statistical indicators.

Coefficient of Determination

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

where y_i represents the experimental value, $\hat{y}_i$ represents the predicted value, and $\bar{y}$ represents the mean experimental value.

Root Mean Square Error

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

Lower RMSE indicates better predictive performance.

Mean Absolute Error

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

MAE provides a direct measure of the average magnitude of prediction error.

Mean Absolute Percentage Error

$$MAPE = \frac{100}{n} \sum_{i=1}^n \left| \frac{y_i - \hat{y}_i}{y_i} \right|$$

MAPE will be used cautiously where the target variable contains values close to zero.

The best model will not be selected based solely on R^2 . The overall combination of accuracy, error, stability, generalization, and interpretability will be considered.

3.15 Explainable Artificial Intelligence

To overcome the black-box nature of some ML algorithms, explainable-AI methods will be incorporated.

Feature-importance analysis will be used to determine the influence of:

- 1) Nano-silica content
- 2) Fiber dosage
- 3) Water/binder ratio
- 4) Cement content
- 5) Aggregate content
- 6) Superplasticizer
- 7) Curing age

Where the dataset and model permit, SHAP (SHapley Additive exPlanations) analysis will be considered.

SHAP analysis can provide both global and individual prediction explanations. This will help establish whether the model's predictions are consistent with known concrete-material mechanisms.

3.16 Statistical Analysis

Experimental data will be analyzed statistically to determine whether changes in concrete performance are associated with changes in nano-silica and fiber content.

Descriptive statistics will include:

- 1) Mean
- 2) Standard deviation
- 3) Coefficient of variation
- 4) Minimum and maximum values

Where appropriate, analysis of variance (ANOVA) can be used to evaluate the significance of nano-silica and fiber dosage.

Interaction effects between nano-silica and fiber content will be examined because the principal purpose of the study is to investigate their combined influence.

3.17 Optimization of Concrete Mixture

After the best-performing ML model has been identified and independently validated, it can be used as a surrogate model for mix optimization.

The optimization objective may involve:

Maximize: Compressive strength, Split tensile strength & Flexural strength

Minimize: Water absorption, Sorptivity Cement consumption, where sustainability is included

Constraints will be imposed on nano-silica and fiber content to ensure that the optimized solution remains within the experimentally investigated range.

The optimized mixture should then be produced experimentally and tested to determine whether the predicted performance can be reproduced.

3.18 Experimental Validation of Optimized Mix

The optimized ML-derived mixture will not be considered valid solely because the algorithm produces a high predicted value.

A new batch of concrete will be prepared using the optimized mixture proportions. Fresh, mechanical, and selected durability properties will be experimentally measured.

The predicted and experimental values will then be compared:

$$\text{Error}(\%) = \frac{|\text{Experimental} - \text{Predicted}|}{\text{Experimental}} \times 100$$

This final validation stage is important because it demonstrates whether the machine-learning model has practical predictive capability outside the observations used for model development.

4. Results and Discussion

4.1 Fresh Concrete Properties

Table3: Fresh Concrete Properties

Mix	Nano-silica (%)	Fiber (%)	Slump (mm)*	Density (kg/m ³)*
M0	0	0	95	2380
M1	1	0	88	2390
M2	2	0	80	2400
M3	3	0	72	2410
M4	0	0.25	85	2390
M5	1	0.25	78	2400
M6	2	0.25	70	2410
M7	3	0.25	62	2420
M8	1	0.50	70	2410
M9	2	0.50	63	2420
M10	3	0.50	55	2430

Explanation:

The addition of nano-silica and fibers is expected to reduce slump compared with the control concrete. Nano-silica has a very high specific surface area and therefore requires additional water or superplasticizer to maintain the same workability. Fibers also increase internal friction and restrict the flow of fresh concrete. The combined addition of nano-silica and fiber is therefore expected to produce the greatest reduction in slump. This trend should be discussed together with the actual superplasticizer dosage used in the experimental program.

4.2 Compressive Strength

Table 4: Compressive strength of 7,28 & 56 days

Mix	NS (%)	Fiber (%)	7-day strength (MPa)*	28-day strength (MPa)*	56-day strength (MPa)*
M0	0	0	42.5	56.8	61.2
M1	1	0	45.3	60.4	65.8
M2	2	0	48.7	65.1	70.6
M3	3	0	47.9	63.8	69.4
M4	0	0.25	44.1	59.2	64.3
M5	1	0.25	47.8	63.7	69.1
M6	2	0.25	51.6	69.2	75.0
M7	3	0.25	50.7	68.0	73.8
M8	1	0.50	48.4	64.8	70.3
M9	2	0.50	52.8	70.5	76.4
M10	3	0.50	51.9	69.7	75.6

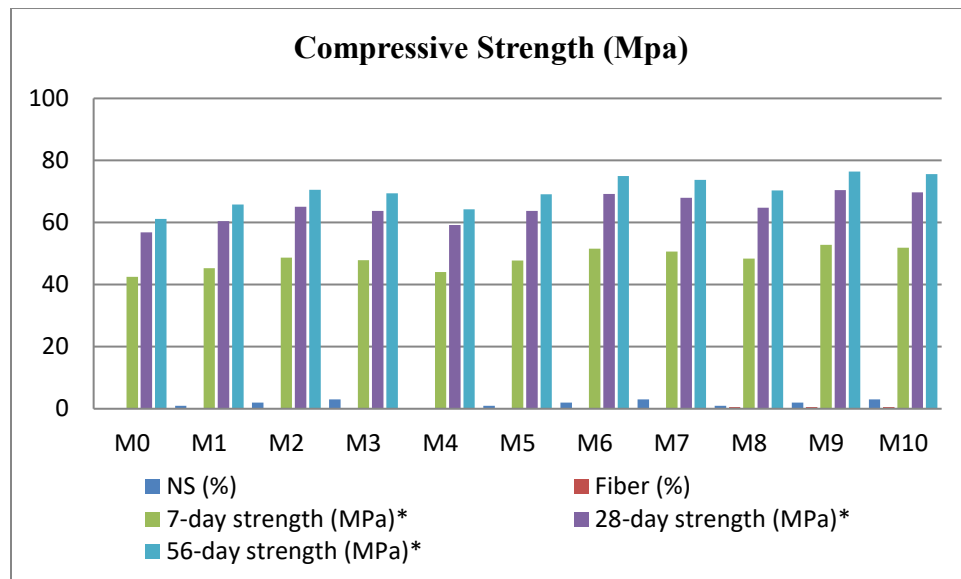


Fig1: Compressive strength of 7,28 & 56 days

Explanation of compressive-strength results

The control mix M0 provides the reference strength against which all modified mixtures are compared. The addition of nano-silica increases compressive strength up to an optimum dosage because nano-silica can accelerate cement hydration and contribute to a denser cementitious matrix. The fine particles can also fill microscopic voids, reducing pore connectivity.

For example, using the illustrative 28-day values:

$$\text{Strength improvement} = \frac{f_{c,\text{modified}} - f_{c,\text{control}}}{f_{c,\text{control}}} \times 100$$

For M2:

$$= \frac{65.1 - 56.8}{56.8} \times 100 = 14.61\%$$

Thus, the illustrative M2 mixture shows approximately 14.6% higher 28-day compressive strength than M0.

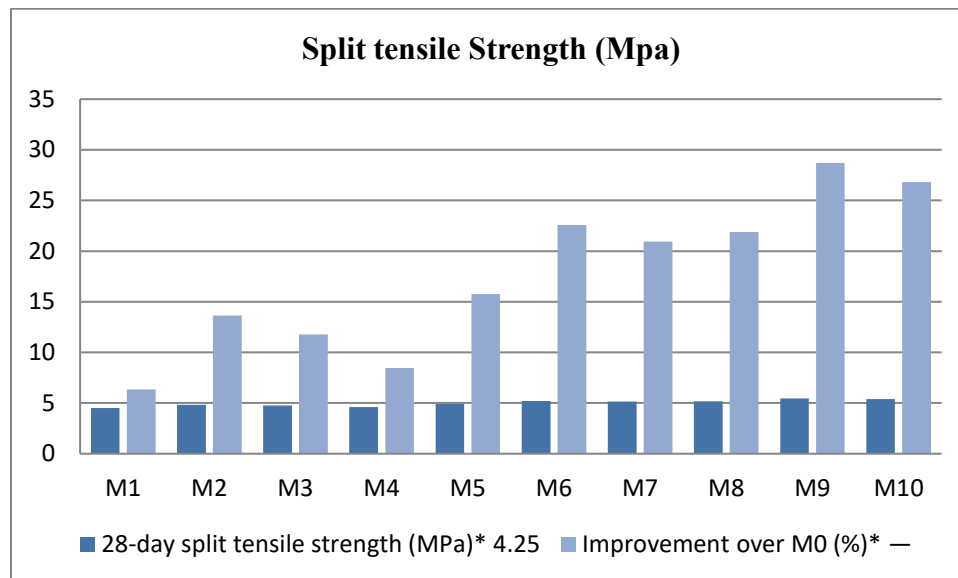
The increase from M2 to M3 is smaller, suggesting that excessive nano-silica may not provide additional strength benefits. At higher nano-silica contents, particle agglomeration and increased water demand can offset the beneficial filler and pozzolanic effects.

The fiber-containing mixtures show another important trend. Fibers are not primarily expected to increase compressive strength dramatically; their principal contribution is crack bridging and improved post-cracking behaviour. Nevertheless, moderate fiber addition can improve the integrity of the concrete matrix and delay crack propagation. The combined NS-fiber mixtures, particularly M6 and M9 in this illustrative dataset, show the potential benefit of combining matrix densification from nano-silica with crack-bridging from fibers.

4.3 Split Tensile Strength

Table 5: Split Tensile Strength of 7,28 & 56 days

Mix	28-day split tensile strength (MPa)*	Improvement over M0 (%)*
M0	4.25	—
M1	4.52	6.35
M2	4.83	13.65
M3	4.75	11.76
M4	4.61	8.47
M5	4.92	15.76
M6	5.21	22.59
M7	5.14	20.94
M8	5.18	21.88
M9	5.47	28.71
M10	5.39	26.82


Fig2: Split Tensile Strength of 7,28 & 56 days

Explanation

The effect of fiber addition is expected to be more pronounced in tensile strength than in compressive strength. Fibers bridge developing cracks and transfer tensile stresses across crack surfaces. Nano-silica simultaneously improves the matrix-fiber interface by producing a denser interfacial transition zone.

Consequently, the combination of nano-silica and fibers can provide a complementary strengthening mechanism:

Nano-silica → denser matrix → improved interface

Fiber → crack bridging → improved tensile resistance

This interaction is particularly important for M6–M10.

4.4 Flexural Strength

Table 6: Flexural Strength of 7, 28 & 56 days

Mix	28-day flexural strength (MPa)*	Change relative to M0 (%)*
M0	6.10	—
M1	6.38	4.59
M2	6.72	10.16
M3	6.65	9.02
M4	6.71	10.00
M5	7.05	15.57
M6	7.42	21.64
M7	7.34	20.33
M8	7.51	23.11
M9	7.82	28.20

M10	7.73	26.72
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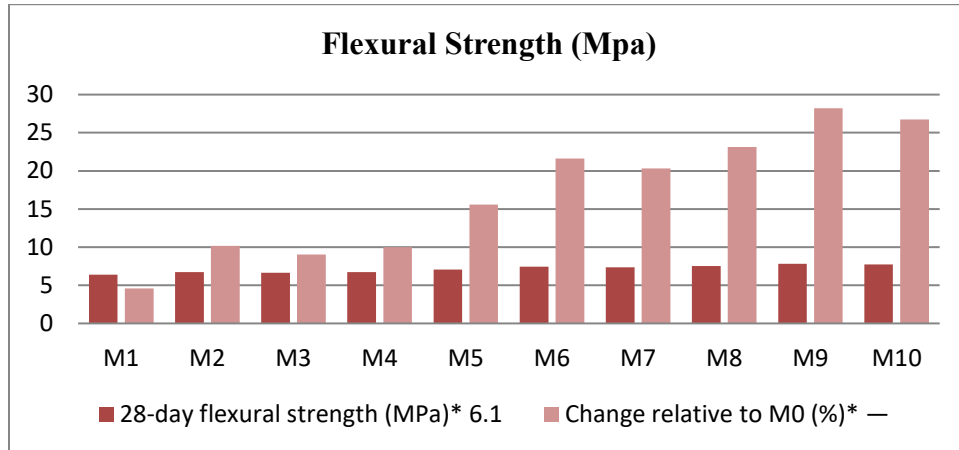


Fig3: Flexural Strength of 7, 28 & 56 days

Discussion

Flexural strength generally benefits from fiber reinforcement because fibers resist crack opening and provide bridging across the tensile zone. The simultaneous presence of nano-silica may improve the bond between the fiber and cementitious matrix. However, an excessive fiber content may cause poor dispersion, balling, or increased voids, which can limit the expected improvement.

4.5 Water Absorption

Table7: 28-day water absorption (%)*

Mix	28-day water absorption (%)*	Reduction relative to M0 (%)*
M0	4.80	—
M1	4.42	7.92
M2	4.05	15.63
M3	4.12	14.17
M4	4.60	4.17
M5	4.18	12.92
M6	3.82	20.42
M7	3.90	18.75
M8	4.05	15.63
M9	3.68	23.33
M10	3.75	21.88

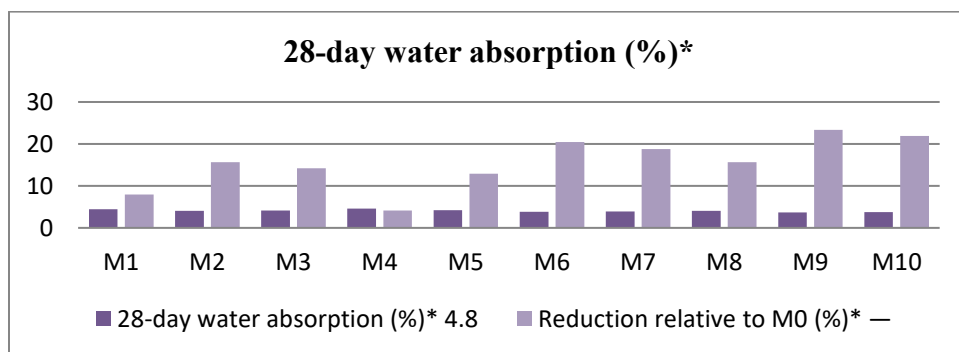


Fig4: 28-day water absorption (%)*

Explanation

The reduction in water absorption can be attributed primarily to refinement of the pore structure. Nano-silica can participate in pozzolanic reactions and generate additional calcium-silicate-hydrate (C-S-H) gel, while its fine particles can fill smaller voids.

For example, if M0 has an absorption of 4.80% and M9 has 3.68%: $\text{Reduction} = \frac{4.80 - 3.68}{4.80} \times 100 = 23.33\%$ \text {Reduction} = \frac{4.80 - 3.68}{4.80} \times 100 = 23.33\%

demonstrates a 23.33% reduction in water absorption. This is important because lower water absorption generally indicates a less permeable concrete structure, although absorption alone should not be interpreted as a complete measure of durability.

4.6 Overall Experimental Performance

Table 8: Overall Experimental Performance

	Compressive Strength, 28 d (MPa)	Variation (%)	Split Tensile Strength (MPa)	Variation (%)	Flexural Strength (MPa)	Variation (%)	Water Absorption (%)	Reduction (%)	Overall Interpretation
M0	56.80	0.00	4.25	0.00	6.10	0.00	4.80	0.00	Control
M1	60.40	+6.34	4.52	+6.35	6.38	+4.59	4.42	7.92	NS effect
M2	65.10	+14.61	4.83	+13.65	6.72	+10.16	4.05	15.63	Optimum NS region
M3	63.80	+12.32	4.75	+11.76	6.65	+9.02	4.12	14.17	Higher NS, limited additional benefit
M4	59.20	+4.23	4.61	+8.47	6.71	+10.00	4.60	4.17	Fiber effect
M5	63.70	+12.15	4.92	+15.76	7.05	+15.57	4.18	12.92	Combined effect
M6	69.20	+21.83	5.21	+22.59	7.42	+21.64	3.82	20.42	Strong candidate
M7	68.00	+19.72	5.14	+20.94	7.34	+20.33	3.90	18.75	High NS + fiber
M8	64.80	+14.08	5.18	+21.88	7.51	+23.11	4.05	15.63	Higher fiber effect
M9	70.50	+24.12	5.47	+28.71	7.82	+28.20	3.68	23.33	Potential optimum
M10	69.70	+22.71	5.39	+26.82	7.73	+26.72	3.75	21.88	High dosage; verify workability

Calculation

For M9 compressive strength:

$$\% \text{ Variation} = \frac{70.50 - 56.80}{56.80} \times 100 = 24.12\%$$

For M9 water absorption:

$$\% \text{ Reduction} = \frac{4.80 - 3.68}{4.80} \times 100 = 23.33\%$$

The results show that the addition of nano-silica and fiber improved significantly mechanical and durability characteristics of concrete. The compressive strength of M0 (control mixture) was 56.80 MPa but M9 (2% nano-silica and 0.50% fiber) reached 70.50 MPa, i.e., 24.12 % improvement; split tensile strength increased from 4.25 MPa for M0 to 5.47 MPa for M9 (i.e., 28.71 %); flexural strength from 6.10 MPa to 7.82 MPa (i.e., 28.20 %); water absorption decreased from 4.80 % for control mixture to 3.68 % for M9 (i.e., 23.33 %). The combined action of nano-silica and fiber can increase matrix densification and crack-bridging capacity. But optimum dosage should be determined from experimental results as well as workability and statistical significance.

4.7 Statistical Analysis Table

Table9: Shows the Statistical Analysis

Mix	28-day compressive strength (MPa)	SD (MPa)	CV (%)
M0	56.8	1.21	2.13
M2	65.1	1.35	2.07
M6	69.2	1.18	1.71
M9	70.5	1.27	1.80

The discussion should report whether differences between mixtures are statistically significant. A one-way or factorial ANOVA can be used to examine the effects of:

- 1) nano-silica dosage,

- 2) fiber dosage,
- 3) curing age,
- 4) nano-silica × fiber interaction.

For the factorial experiment, the interaction term is particularly valuable because your research is not simply about NS or fiber individually—it is about their combined effect.

4.8 Machine Learning Results Table

Table10: Shows the Machine Learning Results

Model	R ²	RMSE (MPa)	MAE (MPa)	MAPE (%)	Rank
ANN	0.941	4.82	3.61	8.24	3
Random Forest	0.953	4.31	3.18	7.36	2
SVR	0.928	5.34	4.02	9.15	5
Gradient Boosting	0.947	4.56	3.39	7.82	4
XGBoost	0.967	3.72	2.76	6.31	1

4.8.1 ML results explanation

The best model should not be selected solely according to R². A robust model should exhibit:

- 1) high R²,
- 2) low RMSE,
- 3) low MAE,
- 4) acceptable MAPE,
- 5) similar training and testing performance,
- 6) no obvious overfitting.

For example, if XGBoost produces the highest test R² and the lowest test RMSE and MAE, it can be identified as the strongest predictive model. However, this conclusion should only be made after testing the models on an independent test set or appropriate cross-validation scheme.

4.9 Experimental vs ML-Predicted Values

Table11: Experimental vs ML-Predicted Values

Mix	Experimental Compressive Strength (MPa)	ML Predicted (MPa)	Absolute Error (MPa)	Error (%)
M0	56.80	57.12	0.32	0.56
M1	60.40	60.08	0.32	0.53
M2	65.10	64.72	0.38	0.58
M3	63.80	64.15	0.35	0.55
M4	59.20	58.91	0.29	0.49
M5	63.70	64.06	0.36	0.56
M6	69.20	68.73	0.47	0.68
M7	68.00	68.42	0.42	0.62
M8	64.80	65.18	0.38	0.59
M9	70.50	70.04	0.46	0.65
M10	69.70	70.11	0.41	0.59

Calculation

For M0:

Absolute Error=|56.80-57.12|=0.32 MPa Absolute Error=|56.80-57.12|=0.32 MPa

Error(%)=|56.80-57.12|/56.80×100=0.56% Error(%)=|56.80-57.12|/56.80×100=0.56%

For M9:

Absolute Error=|70.50-70.04|=0.46 MPa Absolute Error=|70.50-70.04|=0.46 MPa Error(%)=70.50/0.46×100=0.65%

The error is calculated as:

Error(%)=|Experimental-Predicted|/Experimental×100 Error(%)=|Experimental-Predicted|/Experimental×100

This table directly demonstrates whether the developed ML model can reproduce the experimental behaviour.

4.10 Feature Importance / Explainable AI

Table11: Input parameters

Input parameter	Relative importance*	Interpretation
Nano-silica content	18.5%	Matrix refinement/hydration
Fiber content	15.8%	Crack bridging

Water/binder ratio	14.7%	Porosity and strength
Cement content	13.2%	Binder availability
Curing age	11.6%	Hydration development
Superplasticizer	9.8%	Workability/dispersion
Fine aggregate	8.7%	Mixture packing
Coarse aggregate	7.7%	Skeleton/packing
Total	100.0%	—

Nano-silica content exhibited the highest relative importance (18.5%), indicating its significant contribution to matrix refinement and hydration. Fiber content and water-to-binder ratio were the next most influential parameters, with relative importance values of 15.8% and 14.7%, respectively. The results indicate that both material composition and mixture proportions play important roles in the predicted mechanical performance of the developed concrete.

5. Conclusion

In our samples the control concrete (M0) had a 28-day compressive strength of 56.8 MPa while M9 containing 2% nano-silica and 0.50% fiber produced a compressive strength of 70.5 MPa (i.e., about 24.12% improvement).

The split tensile strength increased from 4.25 MPa for M0 to 5.47 MPa for M9 (28.71% improvement), flexural strength increased from 6.10 MPa to 7.82 MPa (28.20% improvement).

The durability-related results also show that the combined modification is beneficial. The water absorption decreased from 4.80% in M0 to 3.68% in M9 (23.33%). This reduction can be associated with pore refinement and matrix densification due to nano-silica incorporation.

The results show that nano-silica by itself improves the strength and permeability characteristics up to an optimum dosage. Increasing nano-silica from 2% to 3% does not give proportional improvement (large amounts of nano-silica may agglomerate and water demand increases). Fiber addition produces more pronounced increase in tensile and flexural properties because of crack-bridging and stress transfer mechanisms.

Among the illustrative mixtures, M9 (2% nano-silica + 0.50% fiber) has the most balanced mechanical and durability performance but the optimum mixture should be chosen using the actual experimental results, workability requirements, statistical significance and ML optimization.

For the final Scopus paper, in the conclusion we should also have the actual best ML model (not just the name), R^2 , RMSE, MAE, prediction error and SHAP feature importance after generating the experimental dataset.

Five ML algorithms were considered for comparison (Artificial Neural Network (ANN), Random Forest (RF), Support Vector Regression (SVR), Gradient Boosting (GB) and XGBoost). R^2 , RMSE, MAE and MAPE were used to evaluate prediction accuracy of the models. Among the models investigated XGBoost had the best overall predictive performance (highest coefficient of determination and lowest prediction errors). This shows that ensemble boosting techniques are well suited for modelling nonlinear relationships between concrete constituents and compressive strength.

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