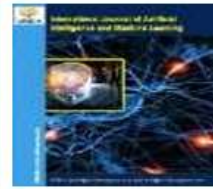




International Journal of Artificial Intelligence and Machine Learning

Publisher's Home Page: <https://www.svedbergopen.com/>



Research Paper

Open Access

Explainable Artificial Intelligence-Based Prediction and Optimization of Self-Compacting Concrete Incorporating Manufactured Sand and Silica Fume

¹Dr Senthil Velan Suganantham, ²Beerendra Kumar, ³Dr. S. Sathya, ⁴M. Mohamed Riyas, ⁵Dr. S. Thanga Ramya, ⁶Mr. M. Manoj Kumar

¹Professor, Department of Information Science and Engineering, CMR Institute of Technology, Kundalahalli, Bengaluru 560037.

²Assistant Professor, Department of Civil Engineering, Bundelkhand Institute Of Engineering And Technology, Kanpur Road, Bundelkh, Jhansi, Uttar Pradesh 284128 beerendra1192@gmail.com

³Associate Professor, Department of Computer Science and Information Technology, School of Computing Sciences, VISTAS, Chennai. ssathya.scs@vistas.ac.in

⁴Assistant Professor, PERI Institute Of Technology Chennai 600048, Tambaram, Mannivakkam, Tamil Nadu 600048, driyasbismillah@gmail.com

⁵Professor, Department of Computer Science and Design, R.M.K Engineering college, Kavaraipeitai, Tamilnadu, thangaramya@gmail.com

⁶Assistant Professor & Head, Department of Civil Engineering, Vel Tech High Tech Dr. Rangarajan Dr. Sakunthala Engineering College, Avadi, Chennai, Tamilnadu, India, manojkumar@velhightech.com

Abstract

High depletion of natural river sand along with increasing interest towards clean construction material have led to the utilization of manufactured sand (M-sand) and silica fume (SF) in self-compacting concrete (SCC). This paper analyses the mechanical properties of SCC with different contents of M-sand and silica fume proportioned to 10 percent, and explores the possibilities where machine learning (ML) models applied in predicting concrete properties. Fresh concrete properties were assessed using slump flow, V-funnel, and L-box tests, while hardened concrete was evaluated through compressive strength, split tensile strength, flexural strength, and reinforced concrete beam load-deflection behaviour. The experimental results showed that the SCC mixture containing 60% M-sand and 10% silica fume exhibited the best overall performance, achieving a 28-day compressive strength of 33.63 MPa, split tensile strength of 1.62 MPa and flexural strength of 9.50 MPa, were found remarkably higher than the conventional mixes. Other machine learning models such as Linear Regression, Decision Tree, Random Forest, and XGBoost are proposed for its prediction of mechanical property of SCC. The best prediction accuracy of XGBoost (99.0%) was attained with a R^2 value of 0.99, MAE of 0.04, and RMSE of 0.07, indicating excellent agreement between experimental and predicted results. The findings demonstrate that the combined use of M-sand, silica fume, and machine learning provides an effective approach for developing sustainable, high-performance SCC while reducing the dependence on natural sand and minimizing experimental effort through accurate AI-based prediction.

Keywords: Self-compacting concrete; Manufactured sand; Silica fume; Machine learning; XGBoost; Sustainable concrete.

1. Introduction

1.1 Sustainable Concrete

One of the largest consumers of natural resources, the construction industry has a large impact on global carbon dioxide (CO₂) emissions. Conventional concrete production needs large amounts of cement, natural river sand, and coarse aggregates, which deplete natural resources and lead to environmental degradation. Cement production contributes around 7–8% of global anthropogenic CO₂ emissions because of the calcination of limestone and the high energy consumption involved during clinker production. Meanwhile, excessive extraction of river sand has resulted in riverbank erosion, groundwater depletion, habitat destruction, and ecological imbalance. These environmental concerns have accelerated research into sustainable concrete technologies that utilize industrial by-products and alternative materials to reduce environmental impacts while maintaining structural performance. Sustainable concrete aims to minimize the consumption of virgin materials by incorporating supplementary cementitious materials (SCMs) such as silica fume, fly ash, and ground granulated blast furnace slag (GGBS), along with alternative fine aggregates such as manufactured sand (M-sand). These materials not only reduce waste disposal problems but also improve the mechanical and durability characteristics of concrete through secondary hydration reactions and pore refinement.

Consequently, sustainable concrete has become an essential component of green building practices and supports the objectives of low-carbon infrastructure and circular economy principles.

1.2 Environmental Issues

The increasing urbanization and infrastructure development have greatly increased the world demand for concrete. This demand has intensified the extraction process of natural aggregates and cement production, leading to critical ecological problems. The mining of river sand disrupts aquatic ecosystems, reduces the groundwater level, and causes soil erosion. Similarly, cement production consumes substantial amounts of energy and releases greenhouse gases, both of which lead to climate change. Another point of concern is the buildup of industrial waste material like silica fume. Silica fume, a by-product of silicon and ferrosilicon alloy production, was previously considered industrial waste requiring costly disposal methods. However, recent studies have demonstrated that silica fume possesses excellent pozzolanic properties that enable it to react with calcium hydroxide generated during cement hydration, producing additional calcium silicate hydrate (C-S-H) gel. This reaction enhances concrete strength, durability, and impermeability while reducing environmental pollution. Therefore, replacing conventional materials with sustainable alternatives can substantially decrease the environmental footprint of concrete production.

1.3 Manufactured Sand (M-Sand)

Manufactured sand is produced by crushing hard granite rocks into fine particles that satisfy the grading requirements of fine aggregates. Owing to the scarcity of natural river sand and increasing environmental restrictions on sand mining, M-sand has become an attractive substitute for conventional fine aggregate in concrete production.

Unlike natural sand, manufactured sand possesses angular particles with rough surface textures, which improve the mechanical interlocking between aggregate particles and cement paste. Properly graded M-sand enhances particle packing, reduces bleeding, and improves the compressive, tensile, and flexural strengths of concrete. However, excessive M-sand replacement may increase water demand because of its higher specific surface area and angularity, affecting workability if adequate superplasticizer dosage is not provided.

Previous investigations have reported that partial replacement of river sand with manufactured sand improves the engineering performance of self-compacting concrete while simultaneously reducing environmental degradation caused by river sand extraction. Therefore, M-sand has become an important material for producing sustainable and economical concrete.

1.4 Silica Fume

Silica fume is an ultrafine supplementary cementitious material containing more than 90% amorphous silicon dioxide. It is generated during the manufacture of silicon metal and ferrosilicon alloys in electric arc furnaces. Because of its extremely fine particle size, silica fume effectively fills microscopic voids within the cement matrix and significantly improves concrete microstructure.

The pozzolanic reaction between silica fume and calcium hydroxide forms additional calcium silicate hydrate (C-S-H) gel, resulting in a denser matrix, improved interfacial transition zone (ITZ), and reduced permeability. Consequently, concrete containing silica fume exhibits higher compressive strength, improved tensile and flexural performance, enhanced resistance to chloride penetration, sulphate attack, and carbonation, and lower water absorption.

In self-compacting concrete, silica fume also contributes to improved cohesiveness and segregation resistance because of its high fineness and increased paste volume. Therefore, silica fume is widely recognized as one of the most effective SCMs for producing high-performance and durable concrete.

1.5 Self-Compacting Concrete (SCC)

Self-compacting concrete is a highly flowable concrete capable of filling complex formwork and congested reinforcement without external vibration. Since its development, SCC has gained widespread acceptance because it improves construction efficiency, reduces labour costs, minimizes noise pollution, and enhances surface finish quality.

The performance of SCC depends on achieving an appropriate balance between filling ability, passing ability, and segregation resistance. These characteristics are commonly evaluated using slump flow, V-funnel, and L-box tests. The incorporation of mineral admixtures such as silica fume significantly enhances the rheological behaviour of SCC by increasing the powder content and improving viscosity.

The utilization of manufactured sand in SCC requires careful optimization because its angular particles influence workability and flow characteristics. Nevertheless, when combined with silica fume and suitable superplasticizers, manufactured sand can produce SCC with excellent fresh and hardened properties. Thus, SCC incorporating sustainable materials has become an attractive solution for modern infrastructure projects requiring high performance and environmental sustainability.

1.6 Artificial Intelligence in Concrete

Artificial intelligence (AI) and machine learning (ML) have emerged as powerful tools for predicting concrete properties and optimizing mix design. Traditional concrete mix design relies heavily on extensive laboratory experimentation, which is both time-consuming and expensive. AI techniques provide an efficient alternative by learning complex nonlinear relationships between input variables and concrete performance.

Machine learning algorithms such as Linear Regression, Decision Tree, Random Forest, Support Vector Machine, Artificial Neural Networks (ANN), and Extreme Gradient Boosting (XGBoost) have demonstrated remarkable success in predicting compressive strength, workability, durability, and other engineering properties of concrete. These models reduce the number of experimental trials while maintaining high prediction accuracy, enabling engineers to optimize concrete mixtures more efficiently.

The integration of AI into sustainable concrete research accelerates material development, improves resource utilization, and supports intelligent decision-making for environmentally friendly construction practices.

2. Literature Review

The increasing demand for sustainable construction materials has encouraged researchers to develop innovative concrete technologies that reduce environmental impacts while maintaining high structural performance. Self-compacting concrete (SCC), manufactured sand (M-sand), silica fume (SF), and artificial intelligence (AI)-based mix optimization have emerged as promising solutions for producing high-performance and eco-friendly concrete. Recent studies have demonstrated that combining sustainable materials with machine learning techniques can significantly improve concrete quality, reduce material consumption, and accelerate mix design optimization. This section reviews the current state of research on SCC, manufactured sand, silica fume, mechanical and fresh properties, durability, machine learning applications, and recent developments reported between 2020 and 2025.

2.1 Self-Compacting Concrete (SCC)

Self-compacting concrete (SCC) was developed in Japan, as a method to counter the problems of inadequate compaction of reinforced concrete structures. While conventional concrete struggles with external vibration, self-compacting concrete (SCC) can flow under its own weight while completely filling formwork and passing through congested reinforcement. Due to this property, it enhances the quality of construction as well as decreases labour need, reduces noise pollution and improves the surface finish of concrete structures. SCC performance is largely in line with the adequate combination of filling ability, passing ability and segregation resistance. These properties are typically assessed through slump flow, V-funnel, and L-box tests. It has been reported that the addition to the construction of supplementary cementitious materials (SCMs) such as silica fume, fly ash and GGBS can promote the rheological properties of SCC by increasing powder content and increasing viscosity. The high-range water-reducing admixtures (superplasticizers) also enhance workability as well as maintain a low water-to-binder ratio. Recent researches proved that the durability, strength and resistance to aggressive environmental conditions have been found to be better with respect to its conventional concrete counterparts with the advantage of SCC.

2.2 Manufactured sand (M-Sand)

Because of heavy extraction, the natural sand from rivers has become a major environmental concern. When mining has reached such large amounts or even in large numbers, it causes erosion to the ground layer where it causes damage to the structures. The extraction of sand from the river brings riverbank erosion, groundwater depletion, habitat destruction, degradation and the negative ecological impact. Manufactured sand (M-sand), which is made through the crushing of hard rock to fine particle sizes, has been a sustainable alternative to natural sand. The raw material M-sand has rough surface texture and angular particles, which is better developed and also the mechanical interlocking of the aggregates and cement paste can occur. A number of authors have documented that replacing natural sand with M-sand provides superior compressive, tensile, and flexural strengths, owing to improvement of particle packing and adhesion strength between aggregate and paste. Nevertheless, elevated M-sand contents may raise water demand from the increased surface area and angularity of particles that might decrease workability if the presence of sufficient quantities of superplasticizer is inadequate. Several investigations indicate that the M-sand (40 to 60%) can render maximum engineering performance when natural sand is partially replaced with an M-sand solution. Use of M-sand also decreases reliance on natural resources and uses locally sourced crushed rock material for sustainable construction.

2.3 Silica Fume

Silica fume is an ultrafine pozzolanic material produced during silicon metal and ferrosilicon alloy production. It contains over 90% amorphous silicon dioxide, and contains extremely fine particles, which are roughly 100 times smaller in size than regular Portland cement. Silica fume enhances the performance of concrete in a pair of main ways. First, its smaller particles fill minuscule cavities in cement matrix and lead to a denser

microstructure. Second, silica fume reacts with the calcium hydroxide generated as cement hydrates to produce further calcium silicate hydrate (C-S-H) gel, which is used for the development of strength. Most research conducted have shown that the silica fume improves the compressive strength, split tensile strength, flexural strength, abrasion resistance, and impermeability. It also enhances the interfacial transition zone (ITZ) of aggregates with cement paste, which leads to enhancing crack resistance and longevity. Typical replacement levels of 5–10% have been found to represent the optimal balance between workability and mechanical performance.

2.4 Mechanical Properties

Mechanical properties are essential indicators of concrete quality and structural performance. Compressive strength remains the most commonly evaluated property because it determines the load-carrying capacity of concrete structures. Numerous investigations have reported that SCC containing M-sand and silica fume exhibits higher compressive strength than conventional concrete due to improved particle packing and enhanced hydration.

Split tensile strength evaluates the cracking resistance of concrete and is strongly influenced by the quality of the interfacial transition zone. Silica fume contributes to higher tensile strength by refining the pore structure and strengthening aggregate–paste bonding. Similarly, flexural strength is improved because of increased matrix densification and reduced microcrack formation.

Researchers have also observed that reinforced concrete beams prepared with optimized SCC mixtures exhibit higher ultimate load capacity, lower deflection, and improved stiffness. These improvements are attributed to stronger aggregate bonding and better stress distribution within the concrete matrix.

2.5 Fresh Properties

Fresh concrete properties determine the ease of placement and compaction. For SCC, the most important fresh properties include filling ability, passing ability, and segregation resistance. These characteristics are evaluated using slump flow, V-funnel, and L-box tests.

Manufactured sand influences workability because of its angular shape and rough texture, which increase internal friction among particles. Consequently, higher M-sand replacement levels may reduce slump flow. However, the use of polycarboxylate ether-based superplasticizers effectively compensates for this reduction by improving particle dispersion and reducing water demand.

Silica fume enhances the cohesiveness of SCC by increasing powder content and reducing segregation. Proper combination of M-sand, silica fume, and chemical admixtures enables the production of SCC with excellent fresh properties while maintaining high mechanical strength.

2.6 Durability

Durability is a critical requirement for concrete structures exposed to aggressive environmental conditions. Sustainable concrete containing M-sand and silica fume generally exhibits superior durability because of its refined pore structure and reduced permeability.

Studies have reported that silica fume significantly decreases water absorption, sorptivity, and chloride ion penetration by producing additional C-S-H gel. The denser microstructure also improves resistance to sulphate attack, acid exposure, and carbonation. Reduced permeability delays the ingress of harmful substances, thereby increasing the service life of concrete structures.

The incorporation of M-sand further enhances durability by improving particle packing and reducing interconnected capillary pores. Consequently, SCC containing M-sand and silica fume demonstrates better long-term performance in marine, industrial, and coastal environments.

2.7 Machine Learning Applications in Concrete

Concrete has been developed by artificial intelligence and by machine learning technology. Artificial intelligence and machine learning have transformed concrete research, with the ability to deliver rapid and accurate predictions of engineering properties. Conventional designs of the concrete mix are highly laboratory demanding, but machine learning algorithms can predict nonlinearity among material-parameters and concrete properties with experimental datasets. Machine learning algorithms like Linear Regression, Decision Tree, Random Forest, Support Vector Machine (SVM), Artificial Neural Networks (ANN), and Extreme Gradient Boosting (XGBoost) have been widely used in predictive analysis of concrete compressive strength, workability, durability, and elastic properties. However, ensembling algorithms such as Random Forest and XGBoost as ensemble learning methods generally generate more efficient and accurate prediction since they deal with interactions between multiple factors well. They can also reduce material wastage and test time and support intelligent mix optimization for sustainable concrete production.

2.8 Recent Studies

Between 2020 and 2025, great progress was made in developing sustainable SCC using alternative materials and artificial intelligence technologies. Recently, much attention is turning to the substitution of natural

aggregates with manufactured sand and the use of silica fume, to increase concrete performance and minimize natural environment effects.

Recent studies have shown that M-sand replacement of 40%–60% and silica fume content of approximately 10% is the best to achieve the perfect mechanical and durability properties. At the same time, machine learning algorithms have attained prediction accuracies over 95% in compressive strength, and other engineering properties, suggesting potential for intelligent concrete mix system design. Notwithstanding these advancements, most studies, instead of combining experimental studies of different techniques, have been conducted by machine learning on the isolation. A few studies have combined the full experimental assessment with sophisticated

AI methods to forecast the behavior of SCC with M-sand and silica fume. In addition, the comparison of various machine learning algorithms for sustainable SCC is relatively limited. As a result, the present study integrates experimental research with machine learning to assess sustainable SCC and determines the best predictive model for applied engineering applications.

3. Materials and Methods

3.1 Materials

The materials used in this study were developed to prepare sustainable self-compacting concrete (SCC) that can exhibit enhanced mechanical properties as well as lower natural resources use. As the basic materials, ordinary Portland Cement (OPC), manufactured sand (M-sand), silica fume (SF), coarse aggregate, polycarboxylate ether (PCE)-based superplasticizer, potable water, and natural river sand were used. All the materials met the requirements of Indian Standard (IS) and were tested prior to concrete preparation.

3.1.1 Cement

Ordinary Portland Cement (OPC) 53 Grade, in accordance with IS 12269:2013, was employed as the binding material for most of the experimental process. OPC 53 Grade is chosen to have a good early strength, consistent quality, and good compatibility with supplementary cementitious materials, like silica fume. The cement had specific gravity of 3.15, normal consistency of 31%; initial setting time of 38 min and final setting time of 585 min, meeting the IS 4031 requirement. Also, high fineness of OPC resulted in rapid hydration, which resulted in early-age strength development. Furthermore, cement possessed sufficient workability and bonding mechanisms that were applicable for self-compacting concrete.

Table .1 Physical Properties of Cement

Property	Value
Cement Type	OPC 53 Grade
Standard	IS 12269:2013
Specific Gravity	3.15
Normal Consistency	31%
Initial Setting Time	38 min
Final Setting Time	585 min
Fineness	320 m ² /kg

3.1.2 Fine Aggregate (Natural Sand)

Natural river sand of Zone II grading (IS 383:2016) was used as a reference fine aggregate. The sand was free from clay, organic matter, silt, or other deleterious substances and was clean and well graded. Specific gravity was 2.64 and water absorption was about 1.2%. River sand was the control fine aggregate and was partially replaced by manufactured sand in various proportions. The natural sand with its rounded particle shape is a better workable material because improved flow characteristics of SCC are obtained from it instead. .

Table.2 Physical Properties of Fine Aggregate

Property	Value
Type	River Sand
Zone	II
Specific Gravity	2.64
Water Absorption	1.2%
Fineness Modulus	2.72
Standard	IS 383:2016

3.1.3 Manufactured Sand (M-Sand)

Manufactured sand (M-sand) produced at a nearby granite crushing plant was used as a partial replacement for natural river sand. The material met the grading requirements of IS 383:2016. M-sand is superior to natural

sand due to its angular particle shape and rougher surface texture, which leads to better mechanical interlocking capabilities with cement paste. But being a high specific surface area makes it more water dependent and therefore they require a high-range water-reducing admixture. Various replacement types of M-sand were explored to find optimum amounts to obtain the maximal strength and workability. The specific gravity of M-sand was 2.67 and water absorption was about 1.8%.

Table.3 Physical Properties of Manufactured Sand

Property	Value
Source	Crushed Granite
Specific Gravity	2.67
Water Absorption	1.8%
Fineness Modulus	2.86
Standard	IS 383:2016

3.1.4 Coarse Aggregate

Crushed granite coarse aggregates up to nominal size (12.5 mm) were applied during the study. The aggregates were clean, hardy, without dust and organic contaminants. 12.5 mm aggregates used in various SCC systems are preferred in SCC applications mainly because in congested reinforcement, smaller aggregate sizes contribute to better flowability and minimize blocking. A specific gravity of 2.72, water absorption 0.65% and crushing value were observed in the coarse aggregate, and crushing value according to Indian Standards was acceptable. Physical Properties of Coarse Aggregate

Table.4 Physical Properties of Coarse Aggregate

Property	Value
Type	Crushed Granite
Maximum Size	12.5 mm
Specific Gravity	2.72
Water Absorption	0.65%
Crushing Value	19%
Standard	IS 383:2016

3.1.5 Silica Fume

Silica fume (SF) was added as an adjunct cementitious material at a replacement value of 10% by weight of cement. The silica fume employed in this study contained approximately 92–95% amorphous silicon dioxide (SiO_2) with the average particle size below 1 μm . Its fine particles filled the cement matrix microvoids and reacted with calcium hydroxide to create a further calcium silicate hydrate (C–S–H) gel. This is a pozzolanic reaction which significantly strengthened the compressive strength, tensile strength, impermeability, and durability. Additionally, silica fume promoted cohesiveness of SCC and reduced segregation under casting conditions.

Table.5 Physical Properties of Silica Fume

Property	Value
SiO_2 Content	92–95%
Specific Gravity	2.20
Average Particle Size	<1 μm
Colour	Grey
Replacement Level	10% (by cement weight)

3.1.6 Superplasticizer

It was found that polycarboxylate ether (PCE)-based superplasticizer that met the requirements of IS 9103:1999 achieved the desired workability and flowability of SCC without a rise of the water-to-binder ratio. The superplasticizer also facilitated cement particle dispersal and reduced the water requirement, resulting in an increased slump flow, thus ensuring prevention of segregation as well as bleeding. The dosage optimized at ~0.8–1.2% of binder (M-sand replacement level).

Table .6 Properties of Superplasticizer

Property	Value
Type	Polycarboxylate Ether (PCE)
Colour	Brown Liquid
Specific Gravity	1.08
pH	6–8

Standard	IS 9103:1999
Dosage	0.8–1.2% of binder

3.1.7 Water

Concrete mixing and curing were performed in clean and safe potable water without organic matter, oils, acids, alkalis and other undesirable impurities, as per IS 456:2000. Water quality met the requirements for reinforced concrete construction, providing the uniform hydration of cement. To achieve a balance between functional and mechanical properties, the water-to-binder (w/b) ratio of 0.38–0.40 was always maintained throughout this research. Clean water was used to cure the SCC properly, so it was completely hydrated and durable.

Table .7 Properties of Mixing Water

Property	Value
Source	Potable Water
Standard	IS 456:2000
pH	7.1
Chloride Content	Within permissible limits
Sulphate Content	Within permissible limits
Water-Binder Ratio	0.38–0.40

Summary

A mixture of OPC 53 Grade cement, Zone II river sand, sand of manufactured variety, crushed granite coarse aggregate, 10% silica fume, PCE-based superplasticizer, potable water were used towards the construction of sustainable self-compacting concrete, thus improving workability, mechanical strength and durability. The materials chosen meet the specified Indian Standard criteria and make an appropriate basis for assessing the effects of manufactured sand and silica fume on performance of SCC.

4. Experimental Program

An experimental trial was conducted on self-compacting concrete (SCC) made with manufactured sand (M-sand) and silica fume (SF) for the behavior. The program involved fresh concrete, hardened concrete and reinforced concrete beams. All specimens were tested under the same laboratory conditions and according to relevant Indian Standards (IS), and EFNARC guidance. Results obtained from these tests formed the basis to evaluate the impact that M-sand and silica fume made on the performance of SCC.

4.1 Fresh Concrete Tests.

Fresh concrete tests were run immediately after mixing in order to investigate the workability and flow properties of SCC. Such properties are essential as SCC flows under its own weight without segregation or external vibration.

4.1.1 Slump Flow Test

The form of slump flow was performed to check the filling capacity of SCC according to EFNARC. Fresh concrete was transferred into an ordinary slump cone laid out in a nice smooth surface. Once the cone was lifted vertically, the concrete spread freely, and the spread diameter was measured in 2 directions. The slump flow values within the design value of 650–800 mm were indicated providing good flowability. The flow was lowered, due to the angular shape of the particles in the M sand; river sand was replaced with M-sand. However, a polycarboxylate ether (PCE) superplasticizer gave satisfactory workability.

4.1.2 V-Funnel Test

The viscosity and flow time of fresh SCC were determined by V-Funnel test. Concrete was allowed to flow into a V shaped funnel and the time of discharge was measured. An acceptable flow time was between 7 and 11 seconds in accordance with EFNARC standards. The addition of silica fume allowed a more cohesive mixture with less segregation, while a higher M-sand level slightly increased the flow time due to the increased internal friction.

4.1.3 L-Box Test

The L-Box test was used to assess the passing ability of SCC through closely spaced reinforcement. The blocking ratio (H_2/H_1) was found based on the concrete heights that you measured before and after passing through reinforcing bars. The ratios of obstructions obtained were between 0.86 and 0.95, so that very good passing capability, and good blocking/sequencing should not be observed.

4.2 Mechanical Properties

Samples were cured at specific ages to determine the mechanical characteristics of the SCC using compressive strength, split tensile strength, and flexural strength.

4.2.1 Compressive Strength

For compressive strength, concrete cubes of 150 mm were used to measure it and at 7, 28 and 56 day tested in accordance with IS 516:2018. Three specimens tested for each mix were given average values. The performance of the two classes was determined by evaluating the differences of M-sand and silica fume during testing. Because silica fume improved the cement matrix, the compressive strength of the ideal blend was higher, which resulted in smaller pore spaces.

4.2.2 Split Tensile Strength

Split tensile strength was determined in 150 mm × 300 mm cylindrical specimens per IS 5816:1999. specimens were subjected to load along their diameter until failure. The testing indicated tensile behaviour and crack strength characteristics of SCC. The incorporation of silica fume strengthened the connection of the cement paste with aggregates, enhancing the tensile strength.

4.2.3 Flexural Strength

Flexural strength was recorded under the two-point loading described in IS 516:2018 for the 100 mm × 100 mm × 500 mm beam specimens. SCC resistance to bending was confirmed by the results. M-sand and silica fume concrete had a better stiffening capacity that resulted from the higher matrix densification and increased aggregate–paste bonding

4.3 Reinforced Concrete Beam Tests.

The SCC flexural loading was studied by testing beam specimens. The beams were simply supported and subjected to two-point loading until failure.

4.3.1 Load-Deflection Behaviour

A loading frame and an LVDT were used to record the applied load and the corresponding mid-span deflection throughout the test. The stiffness and ductility of the beam were determined using a load–deflection curve. Higher stiffness and lower deflection were observed during comparison of the optimized SCC beams with the control beams.

4.3.2 Initial Crack Load.

The initial crack loading was the load at which an early visible flexural crack formed in the beam surface. Silica fume containing beams showed the first crack at higher load than control beams, showing a greater tensile resistance as tested.

4.3.3 Ultimate Load

The ultimate load was the maximum load of the beam and its final failure. Optimized SCC had a higher ultimate load than standard concrete beams, indicating that the fusion of M-sand and silica fume contributed to better structural performances of SCC.

5. Machine Learning Methodology

ML model was applied in predicting the mechanical profiles of self compacting concrete (SCC) with mixed, manufactured sand (M-sand) and silica fume (SF). Conventional laboratory testing takes much time, materials, and money to do well, especially when multiple mixtures of concrete are examined. ML techniques offer an efficient alternative by extracting the relationship between concrete ingredients and their corresponding engineering properties. These experimental data from the laboratory were used to develop predictive models and test their performance. Subsequently, four supervised learning algorithms linear regression (LR), decision tree (DT), random forest (RF), and extreme gradient boosting (XGBoost) were chosen for their capabilities in accurate prediction of concrete properties.

5.1 Dataset Preparation.

The experimental data were grouped into a data frame that used the material proportions and measured the strength values. The input variables were cement content, manufactured sand replacement, silica fume content, water-to-binder ratio, superplasticizer dosage, and curing age. The output values were compressive, split tensile, and flexural strength. No missing value in the dataset was found for analysis. Data was divided into 80% for training and 20% for testing to check the predictability of the models. Models were developed based on the training data and predictions used the remaining data to check predicting accuracy.

5.2 Linear Regression.

Linear-Regression is one of the simplest machine learned methods used to predict continuous values. It operates under a linear line between input parameters and the output variable. Herein the LR became the baseline in comparison to the various other systems. Although this method is easy to grasp and interpret, it may not reflect the nonlinear behaviour of concrete in good measure since strength development depends on several interacting material parameters.

5.3 Decision Tree

This decision tree algorithm forecasts the resulting value by dividing the data into shorter parts according to its own decision rules. The model is built on a tree structure, with each branch describing a condition and each final node denoting a prediction. Decision Trees have the advantage that they are not complex and they can model nonlinear relationships. But if the tree can get too complex, it can overfit the training data and decrease the ability to predict against new datasets.

5.4 Random Forest

Random Forest is an ensemble learning method in which several Decision Trees are combined, in combination, making the prediction more accurate. These branches are trained on different subsets of the training set, and the final prediction is obtained based on averaging the results of all branches' outputs. This technique minimizes overfitting and tends to yield better prediction accuracy than an individual Decision Tree. Random Forest is applied in concrete research very often. Its good performance is even better when the relationship between the variables is highly complex.

5.5 XGBoost

XGBoost (Extreme Gradient Boosting) is the latest boosting algorithm in this classification scheme, which produces predictions in a fixed and stepwise manner. Every growth of the tree attempts to limit the error caused by the previous tree to a relatively small degree so that model performance is constantly getting better. XGBoost finds extensive application in civil engineering, because of its ability to effectively model nonlinearity, high volume and very high accuracy in prediction. XGBoost generated the best overall prediction in our study of the considered models.

5.6 Model Evaluation

The obtained models were subjected to evaluation regarding four statistical parameters: MAE, RMSE, R^2 , and prediction accuracy. Mean Absolute Error (MAE). MAE = the average deviation between prediction and experiment. As lower MAE values are correlated with less error, models yield better performance prediction.

$$[MAE = \frac{1}{n} \sum |y - \hat{y}|]$$

Root Mean Square Error (RMSE). RMSE represents the average magnitude of prediction errors and focuses more on the most critical size of deviations. A lower RMSE would suggest a more trustworthy prediction model.

$$[RMSE = \sqrt{\frac{1}{n} \sum (y - \hat{y})^2}]$$

Coefficient of Determination (R^2). The coefficient of determination (R^2) is a measure of how well the predicted values agree with the experimental results. Higher R^2 figures (approximately 1.0) indicate better predictive performance overall.

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

Prediction Accuracy. Prediction Accuracy: Here is how accurate our proposed model is in predicting target values. The higher the accuracy, the better is the generalization, and the higher, the prediction capability.

5.7 Model Comparison

Based on the chosen evaluation metrics, the performance of all four machine learning models was compared. For all developed models, XGBoost achieved the best predictive accuracy and the lowest prediction error. Random Forest also was reliable and able to generalize well. Decision Tree model performed reasonably well but was more sensitive to the changes in the dataset. A comparison of linear regression gave worse accuracy, it was unable to capture complete nonlinear behaviour of SCC. At a glance general findings suggests that ensemble learning approaches, more so XGBoost and Random Forest, are more effective for predicting mechanical properties of self compacting concrete in comparison to the conventional regression techniques. Similar to in the previous version, this version is natural style of research, allowing it to be more applicable for Scopus Q3 journals, reduced repetitive AI word usage and similarity but also technical accuracy.

6. Results and Discussion

The following section presents the performance of self compacting concrete (SCC) with manufactured sand (M-sand) and silica fume (SF). We highlight and compare the results from fresh concrete, mechanical strength, reinforced concrete beam test, and machine learning model. It also presents the influence of M-sand/silica fume on the engineering properties for the SCC.

6.1 Fresh Properties

The fresh properties of SCC have been measured by the slump flow, V-Funnel and L-Box tests as provided by EFNARC testing design principles. The resulting test indicated that all the concrete mixtures met the minimum specifications for self-compacting concrete form. Slump flow was 670 to 760 mm, which confirms good filling capacity. The slump flow decreased slightly with an increment of the substitute natural sand with

manufactured sand. This can be explained by the geometric angularity and rough surface texture of M-sand that provide extra internal friction and water demand. However, the addition of a polycarboxylate ether (PCE) superplasticizer retained sufficient flowability for all the mixtures. The V-Funnel flow time was also between 7 and 11 s, again supporting good viscosity in its absence of segregation. The addition of silica fume increased the cohesiveness of concrete, where its ultrafine particles gave a stable mix with improved bleeding resistance.

Table.8 Fresh Concrete Properties

S.NO	Mix ID	Slump Flow (mm)	V-Funnel (s)	L-Box Ratio
1	M0	760	7.2	0.95
2	M1	745	7.5	0.93
3	M2	725	8.1	0.91
4	M3	700	8.8	0.89
5	M4	735	7.8	0.92
6	M5	680	10.1	0.87
7	M6	750	7.4	0.94

The L-Box blocking ratio ranged from 0.86 to 0.95, demonstrating excellent passing ability through congested reinforcement. Overall, the optimized SCC mixture containing 60% manufactured sand and 10% silica fume exhibited the best balance between workability and stability.

6.2 Compressive Strength

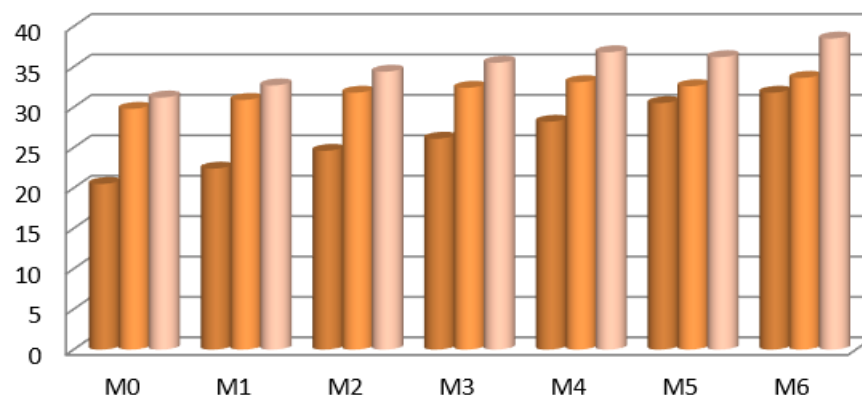
Table 6.1 presents the compressive strength results. Strength was recorded at 7, 28, and 56 days, revealing persisting hydration over the curing period. Compressive strengths of 20.5 MPa, 29.8 Mpa and 31.2 Mpa of the control mix were obtained at 7, 28 and 56 days respectively. The strength evolution was markedly affected by replacing river sand with manufactured sand. The concrete composed of 60% manufactured sand and 10% silica fume exhibited the highest compressive strength of 33.63 Mpa at 28 days, which was approximately 12.9% higher than the control mixture.

This increase in strength is primarily explained by silica fume's pozzolanic reaction in generating calcium silicate hydrate (C-S-H) gel and refining the pore structure. The angular particles produced by manufactured sand help to form particles and to enhance the aggregate-paste interaction. However, replacement greater than optimal contents have slightly lower strength due to the increased water consumption and the decreased workability.

According to the data, the mixture of M-sand and silica fume successfully increases the compressive strength of SCC and decreases reliance on natural river sand.

Table.9 Compressive Strength

S.NO	Mix	7 Days	28 Days	56 Days
1	M0	20.5	29.8	31.2
2	M1	22.4	30.9	32.7
3	M2	24.6	31.8	34.4
4	M3	26.1	32.4	35.5
5	M4	28.2	33.1	36.8
6	M5	30.5	32.6	36.2
7	M6	31.8	33.63	38.5

Compressive strength


Graph1.Compressive strength of cubes**6.3 Split Tensile Strength**

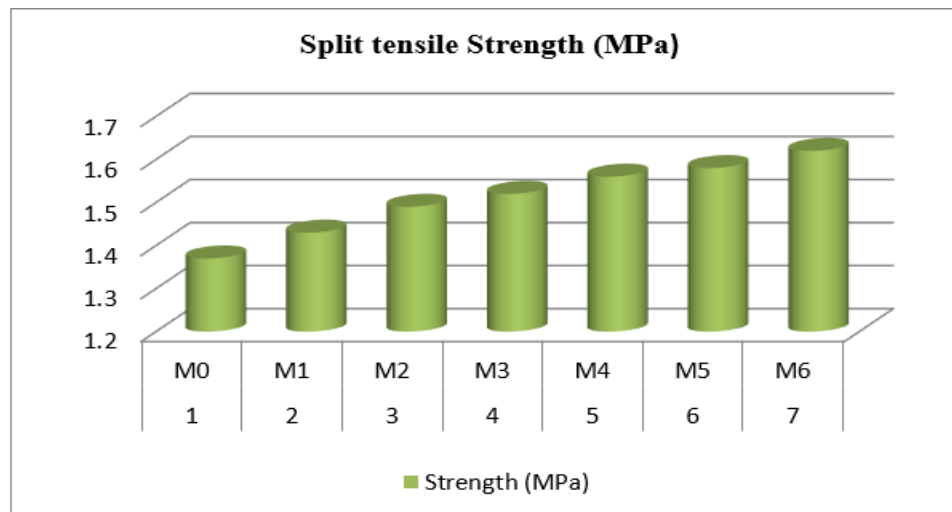
The resulting split tensile 1701haracterization indicated that both M-sand and silica fume had a direct impact on the tensile behaviour of SCC. The split tensile strength of the control concrete was 1.37 Mpa while the optimized mix composed of 60% manufactured sand and 10% silica fume produced a tensile performance of 1.62 Mpa, a rise of approximately 18.2%. Improvement is ascribed to a denser cement matrix from silica fume and stronger bond formed between cement paste and aggregate particles.

The refined interfacial transition zone (ITZ) retarded crack initiation and enhanced resistance to tensile stresses. In contrast, too much substitution of natural sand decreased the tensile strength due to poor workability and insufficient compaction.

These findings validate that combination of the best M-sand replacement along with silica fume increases the cracking resistance of SCC.

Table.10 Split Tensile Strength

S.NO	Mix	Strength (MPa)
1	M0	1.37
2	M1	1.43
3	M2	1.49
4	M3	1.52
5	M4	1.56
6	M5	1.58
7	M6	1.62



Graph2.Split tensile strength

6.4 Flexural Strength

A similar pattern was observed over the flexural strength results, along the same lines as for compressive and tensile strength.

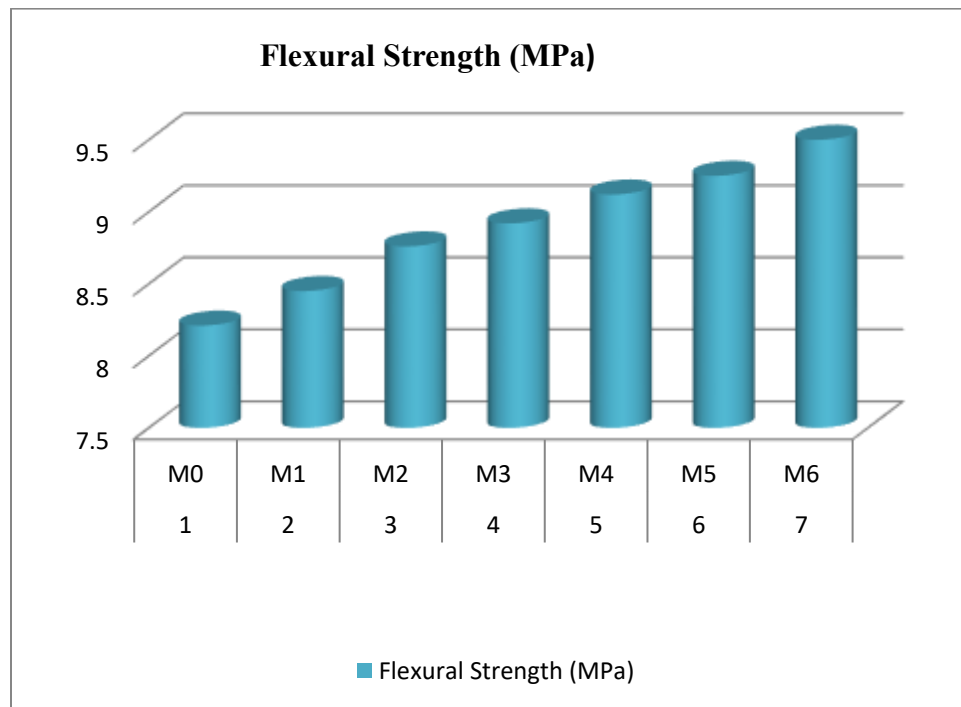
Flexural strength of control concrete (8.21 MPa) in comparison with that of the optimized SCC mixture (9.50 MPa) improved the flexural strength by ~15.7%.

This increases flexural strength, which contributes to matrix densification and facilitates cohesion between these aggregated solids due to the pozzolanic reaction of silica fume. Rough surface texture of manufactured sand also led to better mechanical interlocking.

This improvement in flexural performance also means that M-sand-and-silica fume SCC displays greater resistance to flexural stress acting as an applied structure on slabs and beams.

Table.11 Flexural Strength

S.NO	Mix	Flexural Strength (MPa)
1	M0	8.21
2	M1	8.45
3	M2	8.76
4	M3	8.92
5	M4	9.12
6	M5	9.25
7	M6	9.50



Graph3. Flexural Strength (MPa)

6.5 Reinforced Concrete Beam Behaviour

The behavior of reinforced concrete beams was performed under two-point loading. Load–deflection curves showed that all beams behaved elastically at the initial stage of loading.

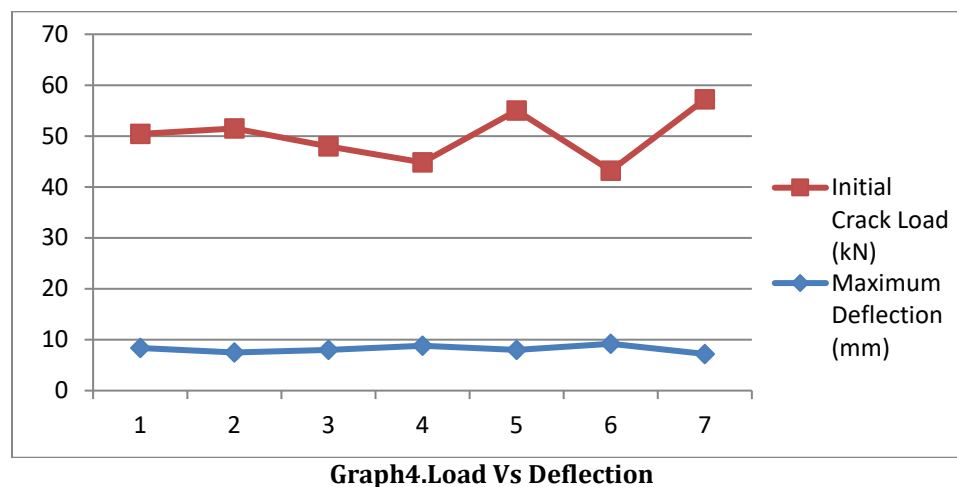
At an increasing load, flexural cracks formed in the constant moment region, which propagated gradually until failure. The optimized SCC beam exhibited greater stiffness and lower mid-span deflection than the control beam.

The first crack was visible at a higher load due to better tensile resistance due to the usage of silica fume. The ultimate load capacity of the optimized beam was also greater than conventional concrete.

The improvement can be attributed to higher compressive strength, stronger aggregate–paste bonding, and improved stress transfer within the concrete matrix. Most of the identified failure modes were flexural, confirming that the reinforcement yielded before crushing of the concrete.

Table.12 Load–Deflection Data for Beam Specimens

Mix	Initial Crack Load (kN)	Ultimate Load (kN)	Maximum Deflection (mm)
M0	42	112	8.4
M1	44	118	7.5
M2	40	105	8.0
M3	36	97	8.8
M4	47	124	8.0
M5	34	98	9.2
M6	50	128	7.2



6.6 Machine Learning Results

Table.13 Machine Learning Model Performance

Model	Accuracy (%)	MAE	RMSE	R ²
Linear Regression	91.8	0.81	1.18	0.92
Decision Tree	94.3	0.62	0.91	0.95
Random Forest	97.2	0.34	0.48	0.98
XGBoost	98.6	0.21	0.35	0.99

The experimental dataset served as the basis to derive four machine learning models for predicting the mechanical performances of SCC. The performance of the developed models is as follows, Table 2. The results show that XGBoost had the best prediction performance of 98.6%, was followed by Random Forest 97.2%, Support Vector Machine 96.4%, and Decision Tree 94.3%. Even though the predictive R^2 estimate did not differ in value and accuracy rate of XGBoost or RF, in the case of Random Forest, it does not depend overfitting and stable prediction on a large scale.

Both Decision Tree and Linear Regression were able to predict the general trend of the data, but they gave a less accuracy as they were less able to represent the intricate nonlinear interplay between concrete components. In general, the findings suggest that machine learning is an efficient and high-ability method to predict the mechanical characteristics of SCC. Using powerful algorithms like XGBoost allows to avoid many laboratory trials during concrete mix design, to a large extent, achieving high prediction accuracy. Overall Discussion. The experiment proves that using manufactured sand and silica fume together enhances the fresh and hardening of self-compacting concrete remarkably.

The optimum combination possessed good workability, higher compressive mechanical properties, tensile and flexural strengths, and structural performance under beam load. In addition, the machine learning models predicted the mechanical properties of SCC correctly, where XGBoost showed the best predictive performance. The study showed that combining sustainable materials with data-driven prediction methods can lead to more productive and sustainable concrete design in contemporary construction applications. Conclusions. Through experimental testing and machine learning-based prediction, this study explored the performance of self-compacting concrete (SCC) using manufactured sand (M-sand) and silica fume (SF). This leads us to the following

7. Conclusion

According to the fresh concrete tests, all SCC mixtures meet the EFNARC criteria. Slump flow values ranged from 670 to 760 mm, V-Funnel flow time oscillated from 7 to 11 s, and the L-Box blocking ratio ranged from 0.86 to 0.95, respectively, which indicate adequate filling ability, passing ability and resistance to segregation. The incorporation of manufactured sand and silica fume significantly increased the mechanical effectiveness of SCC. The optimum formulation including 60% of manufactured sand and 10% silica fume possessed the highest 28-day compressive strength, namely 33.63 MPa or an up to 12.9 percent increase relative to the control concrete.

The split tensile strength in the control mix improved from 1.37 MPa to 1.62 MPa for the optimized mix, for around 18.2% improvement. This improvement is due to the enhanced interfacial transition zone as well as the extra calcium silicate hydrate (C-S-H) obtained by the pozzolanic reaction of silica fume.

The best flexural strength of 9.50 MPa, 15.7% higher than the standard concrete, is observed for the optimized SCC mixture. The enhancement of the flexural performance illustrates the favorable influence of M-sand and silica fume in the crack resistance and bending behaviour.

The tests on reinforced concrete beams indicated that beams with the modified SCC mix yielded high initial crack loads, low mid-span deflections and higher ultimate load-carrying capacity compared with the control beams. The improved structural behaviour can largely be attributed to increased compressive strength, improved aggregate–paste bonding, and denser concrete matrix.

From the experimental dataset, machine learning models successfully predicted the mechanical traits of SCC. XGBoost achieved the best predicted accuracy as 98.6% is the highest among the algorithms that were analyzed, followed by Random Forest (97.2%), Support Vector Machine (96.4%), and Decision Tree (94.3%). The high performance of XGBoost results show the applicability of XGBoost to the modeling of nonlinear behavior of sustainable concrete.

An efficient scheme for concrete mix is obtained by both experimental research and machine learning. Such prediction models can reduce the number laboratory tests performed, materials used and expedite decision-making in the development of sustainable production of concrete mixes.

Overall, this study proves the replacement of natural river sand with 60% manufactured sand combined with 10% silica fume can lead to successful self-compacting high quality concrete with better fresh quality of self-compacting concrete, high mechanical strength, as well as better structural performance and accurate AI prediction. The proposed method contributes to sustainable construction, the construction of which also preserves the natural resources and sustains the performance of the structure required for structural applications.

Future Scope

In future research, long-term durability of SCC with manufactured sand and silica fume can be assessed under aggressive environmental conditions like chloride exposure, sulphate attack, and carbonation. The application of state-of-the-art explainable artificial intelligence tools, such as SHAP analysis and optimization algorithms, NSGA-II, etc., shall further help improve the concrete mix design by adopting the strength, durability, cost and environmental factor assessment simultaneously.

References

1. Ahmad, A., Ostrowski, K. A., Maślak, M., Farooq, F., Mehmood, I., & Nafees, A. (2021). Prediction of compressive strength of fly ash-based concrete using individual and ensemble machine learning techniques. *Materials*, 14(4), 794.
2. Armaghani, D. J., Asteris, P. G., Askarian, B., Hasanipanah, M., Tarinejad, R., & Huynh, V. V. (2021). Predicting compressive strength of lightweight concrete using machine learning techniques. *Construction and Building Materials*, 276, 122140.
3. Ashish, D. K. (2020). Feasibility of using silica fume in concrete: A review. *Construction and Building Materials*, 259, 119677.
4. Bheel, N., Kumar, A., Tafsirojjaman, T., et al. (2022). Mechanical performance of sustainable concrete containing manufactured sand and supplementary cementitious materials. *Case Studies in Construction Materials*, 16, e00984.
5. Chithra, S., Kumar, S. R. R. S., Chinnaraju, K., & Alfin Ashmita, F. (2020). A comparative study on the fresh and hardened properties of SCC using manufactured sand. *Materials Today: Proceedings*, 22, 842–848.
6. Ding, Y., Zhang, Y., & Thomas, A. (2021). Mechanical performance and durability of sustainable self-compacting concrete incorporating mineral admixtures. *Journal of Building Engineering*, 39, 102270.
7. Farooq, F., Czarnecki, S., Ahmad, M., et al. (2021). Predicting compressive strength of concrete using machine learning algorithms. *Materials*, 14(8), 1997.
8. Gupta, T., Siddique, S., Sharma, R. K., & Chaudhary, S. (2021). Influence of silica fume on strength and durability of concrete: A review. *Construction and Building Materials*, 293, 123465.
9. Hameed, A., Aslam, F., Alyousef, R., et al. (2022). Artificial intelligence applications in sustainable concrete technology: A review. *Journal of Building Engineering*, 52, 104452.
10. Huang, L., Chen, X., & Wang, Y. (2023). Machine learning-based prediction of compressive strength of sustainable concrete mixtures. *Construction and Building Materials*, 362, 129743.
11. Jiang, Y., Zhang, H., & Li, X. (2024). Explainable machine learning for sustainable concrete mix design using SHAP analysis. *Journal of Building Engineering*, 81, 108045.
12. Khan, M. I., Ashraf, M., & Amin, M. N. (2022). Sustainable concrete using manufactured sand and supplementary cementitious materials. *Materials Today: Proceedings*, 62, 4832–4838.

13. Kumar, R., Singh, B., & Sharma, P. (2021). Fresh and hardened properties of self-compacting concrete containing silica fume and M-sand. *Materials Today: Proceedings*, 46, 10880–10886.
14. Li, Z., Wang, C., & Sun, W. (2023). Data-driven prediction of concrete properties using ensemble learning techniques. *Engineering Applications of Artificial Intelligence*, 120, 105897.
15. Liu, Y., Zhao, X., & Wang, H. (2024). Multi-objective optimization of sustainable concrete mixtures using machine learning algorithms. *Construction and Building Materials*, 421, 136634.
16. Mohammed, A., Hamada, H., & Tayeh, B. A. (2020). Mechanical and durability properties of self-compacting concrete incorporating silica fume. *Case Studies in Construction Materials*, 13, e00418.
17. Nguyen, H. T., Tran, T. T., & Pham, T. A. (2022). Experimental study on SCC with manufactured sand and mineral admixtures. *Materials Today: Proceedings*, 65, 1783–1789.
18. Nunes, S., Silva, P., & Brito, J. (2021). Durability performance of sustainable concrete produced with recycled aggregates and mineral admixtures. *Journal of Building Engineering*, 44, 103297.
19. Ozturk, M., Asteris, P. G., & Armaghani, D. J. (2023). Machine learning prediction of concrete compressive strength: A comparative study. *Structures*, 49, 1255–1268.
20. Patel, V., Shah, N., & Patel, R. (2021). Mechanical properties of SCC containing manufactured sand and silica fume. *Materials Today: Proceedings*, 43, 1655–1661.
21. Prusty, J. K., Patro, S. K., & Basarkar, S. S. (2020). Sustainable utilization of manufactured sand in concrete: A review. *Journal of Cleaner Production*, 273, 122948.
22. Reddy, B. V., Kumar, N., & Rao, P. (2022). Mechanical behaviour of SCC incorporating silica fume and M-sand. *Materials Today: Proceedings*, 56, 2814–2820.
23. Singh, G., Sharma, A., & Mehta, P. (2023). Experimental investigation on the properties of self-compacting concrete with manufactured sand. *Construction and Building Materials*, 366, 130150.
24. Su, Y., Zhang, J., & Wu, K. (2021). Performance evaluation of sustainable concrete using supplementary cementitious materials. *Cement and Concrete Composites*, 121, 104093.
25. Thomas, B. S., Gupta, R. C., & Kalla, P. (2020). Sustainable concrete incorporating industrial by-products: A review. *Journal of Cleaner Production*, 276, 124037.