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Fiber reinforced self compacting concrete workability properties prediction and optimization of mix using machine learning modeling

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ABSTRACT

Self Compacting Concrete (SCC) is an engineered concrete manufactured in such a way that it can compact itself independently, without any external vibrations or equipment. The self-weight of the SCC is specifically higher than that of the Conventionally Vibrated Concrete (CVC) because of more fines in the SCC. The fines help to achieve self-compaction, but at the same time, it creates more shrinkage in the SCC. The fibers were used in the SCC to reduce these shrinkages. This investigation uses, various percentages of natural kenaf fibers such as 0.1%, 0.2%, 0.3% and 0.4%. Due to this variation in the fiber fractions, the workability properties are affected in the SCC. If the workability gets affected, the concrete does not have the self-compaction property and behaves as CVC. Hence the current research focuses on the SCC Workability Properties (WP) and optimization of SCC mix utilizing machine learning techniques. Considering the advantages of past research, a model was developed with a fusion approach that incorporates Principal Component Analysis (PCA) for SCCWP. Initially, the dataset is processed with the help of standardization using an SCC mix. The processed output is fed into principal component analysis for a dimensional shift from high to low. Then the low dimensional data is given as input to the effect of various workability properties of Fiber Reinforced Self Compacting Concrete (FRSCC) which was modeled using a Support Vector Machine (SVM) and Logistic Regression (LR). A comparison has been made, logistic regression produces a more reliable outcome compared to support vector machine in terms of all the evaluation metrics used.

Keywords: Self Compacting Concrete; Fiber Reinforced; Machine Learning; Optimization; Logistic Regression; Support Vector Machine.

1. INTRODUCTION

Self Compacting Concrete (SCC) is a novel type of concrete that is placed and compacted without the use of vibration [1]. Even when reinforcements are congested, they can flow under their self-weight, filling formwork and achieving complete compaction. Similar to the Conventionally Vibrated Concrete (CVC), the SCC has the same durability and engineering attributes. [2]. Vibration-free and compaction-free concrete have been produced in Europe since the early 1970s for congested reinforcements. The various cementitious material utilizations reduced the quantity of the cement required so, that the CO_2 emission is reduced due to the cement production [3]. SCC can be designed to meet density, workability, strength, and durability requirements. The increased powder content in SCC may induce more plastic shrinkage or creep than CVC [4]. It is important to take these things into account when developing and defining SCC. Currently, there is a lack of understanding of these factors, and this study focuses primarily on these issues. SCC enables rapid concreting, reducing construction time and allowing for easier flow around congested reinforcing due to supplementary cementitious materials [5]. Higher levels of finish and durability are feasible because of the high degree of homogeneity, few voids, and consistent concrete strength that may be achieved with SCC fluidity and resistance to segregation [6]. SCC is frequently manufactured with a low water-cement ratio, which enables strong initial strength, prior demolding, and speedier service use. Eliminating vibrating machinery enhances the working conditions at construction sites and precast locations where the concrete is poured by minimizing worker exposure to noise and vibration. SCC is an extremely appealing option for precast and other works [7]. The most recent information available to producers and customers at the time had been provided by EFNARC's "Specification & Guidelines for Self-Compacting Concrete," which was published in 2002 [8].

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The fibers were added in the SCC, to reduce the brittle property and enhance the tensile properties [9]. Kenaf fiber is a natural fiber that is available in India over almost all the states. In ancient days across India, the kenaf fibers were used for connecting wood planks etc. These kenaf fibers have good mechanical properties. The kenaf fiber creates a better bond between the cement matrix and it is an effective green waste product for the construction industry [10]. The natural kenaf fibers are more effective in the enhancement of the shrinkage properties of the composites and it is free of cost since it is a waste product accumulated in large quantity [11]. It has more durability and strength when compared to other natural fibers. These kenaf fibers have good mechanical properties. However, the alkali treatments required for natural fibers to improve all these properties [12].

The Machine learning algorithms used in Artificial Intelligence (AI) are broadly categorized into four types (i) Supervised and (ii) Unsupervised (iii) Semi-Supervised (iv) Reinforced learning [13]. Each modeling algorithm has specific features and applications. Machine Learning is a powerful computation tool since it requires less time and more accuracy due to the training of the model compared to traditional computational modeling [14]. Since material science research has labeled or targets for predictions, supervised learning modeling is used. Supervised learning has many algorithms like linear regression, logistic regression and KNN etc. Linear regression is used for the continuous target values. For the prediction of strength and durability of the concrete linear regression (Simple linear or Multilinear regression) is used since the strength values are continuous [15]. Logistic regression is a simple tool when modeling the dependence of binary and multiple-class response variables on one or more independent variables [16]. Mathematical modeling is employed to evaluate the strength and durability properties of the concrete with various admixtures at various partial replacements [17].

The workability testing procedure for the SCC is different from the CVC. In CVC, only the slump height decides the workability parameter, whereas, in the case of SCC it has to satisfy three properties like flowability, passing ability, and segregation resistance [18]. Cement-based nanocomposites are an active area of study, specifically using AI techniques to evaluate and predict cement-based materials mechanical characteristics [19, 20, 21]. Also, some scientists have tried using ML techniques to assess the effectiveness of cement-based nanocomposites. As an illustration, the mechanical properties of cement-based materials can be predicted using artificial neural networks (ANN) as well as other genetic optimization techniques. To predict how strong recycled aggregate concrete will be, KHADEMI *et al*. [22] studied the usage of multiple linear regression and adaptive neural fuzzification systems. Similarly, in a subsequent investigation, KHADEMI and JAMAL [23] utilized the same method to forecast the strength development of the concrete made from recycled aggregate after two weeks of curing. The aforementioned method yielded findings that were in agreement with the projected ones, proving the viability of using machine learning approaches to foretell the efficiency of cemented-based materials. Unfortunately, there is little data to back up the claims that artificially intelligent approaches may accurately and efficiently increase the strength properties of cemented-based composites that employ mining waste for aggregates. In addition, it is worth noting that the aforementioned computer vision methods have been effectively adapted towards the forecast of the concrete structures, although these investigations still have the constraints of uncertainty, being moment, and low efficiency.

The field also makes use of more sophisticated algorithms like the random forest, support vector machine, and decision tree. It's important to highlight that almost all machine learning algorithms can provide reliable predictions, but there is little study on how different models affect reliability. The aforementioned methods vary in their sensitivity to various types of datasets and features.

In this research work the SCC was produced with various proportions of fly ash for enhancing the workability properties and kenaf fiber for enhancing the strength properties of the concrete. Based on this for various mix proportions, the workability parameters are measured in the fresh Self Compacting Concrete. These workability parameters help determine the nature of the concrete due to fly ash and kenaf fiber. Then these workability parameters are converted into categorical values for the logistic regression modeling. The logistic regression algorithm is used for the classification of concrete based on the workability parameters. Modeled the hypothesis for prediction the whether the given mix proportions are achieving self-compaction or not based on the LR. The LR is primarily a binary classification hypothesis like 0 or 1, True or False or Yes or No. Based on that the hypothesis was created for predicting workability properties of SCC. Generally, Machine Learning algorithms required data sets. The data set was prepared based on the various mix proportions with their relevant workability parameters.

2. MATERIALS AND METHODS

The materials used for the production of Fiber Reinforced Self Compacting Concrete (FRSCC) are listed below.

2.1. Cement

The Ordinary Portland Cement (OPC) 53 Grade were used in the SCC mix which satisfying the IS 12269-2013 [24]. The cement-specific gravity is 3.15 and 5% fineness.

2.2. Fly ash

The class F-Fly Ash obtained from the Ennore-Chennai plant is utilized in the research work and satisfies the IS 3812(1)- 2013 [25] which has a specific gravity of 2.12.

2.3. Fine aggregate

Locally available natural sand as a Fine Aggregate contains more fines to satisfy the SCC criteria. The specific gravity of the sand is 2.53 (Zone II), and it complies with IS 383-2016 [26].

2.4. Coarse aggregate

Locally available natural Coarse Aggregates of 12 mm size with a specific gravity of 2.63 is used in the research work. The unit weight is 1610 kg/m^3.

2.5. Water

The water free from impurities and salts is used for mixing the SCC.

2.6. Super plasticizer

The Polycarboxylate Ether based Super Plasticizer is used to obtain the flow of SCC it has a specific gravity of 1.1, which includes the viscosity modifying agent.

2.7. Kenaf fiber

In this work, the Kenaf Fiber is obtained from the villages near Villupuram district, Tamil Nadu, India. The naturally available Kenaf Fiber is treated with 5% NaOH in the laboratory as shown in Figure 1. The NaOH alkali treatment helps enhance the natural fiber's mechanical properties and compatibility properties in the composite matrix [27]. The diameter of the fiber ranges from 0.8 to 1.2 mm, and the length of the fiber ranges from 20 mm to 25 mm (20 to 25 aspect ratio) and the proportions are based on clause 4.5.7 of IRC SP:46-2013 [28].

Figure 1: Kenaf Fiber.

3. METHODOLOGY

This section explores various techniques that are used to predict self-compacting concrete workability. A dataset has been created to analyze the efficacy of the proposed framework, which is given in Table 1 and Table 2. The raw dataset is initially preprocessed using the standardization technique (SSC-Mix). Then, check whether high dimensions exist over the dataset. If so, the dataset is fed as input to the PCA. Then, the transformed output is provided as input to the logistic regression and support vector machine. Finally, the most feasible model is determined with the help of various performance evaluation metrics. The proposed architecture is represented in Figure 2.

4. EXPERIMENTAL INVESTIGATION

4.1. Mix proportions of self-compacting concrete

The mix proportions for SCC are designed based on the IS10262-2009 [29] and IS 456-2000 [30] recommendations for SCC. The mix design proportions keep fine and coarse aggregate fractions constant and the sample mix is represented in Figure 3. The various percentages of partial replacement of cement by fly ash and the addition of various percentages of the alkali-treated kenaf fiber are presented in Table 1.

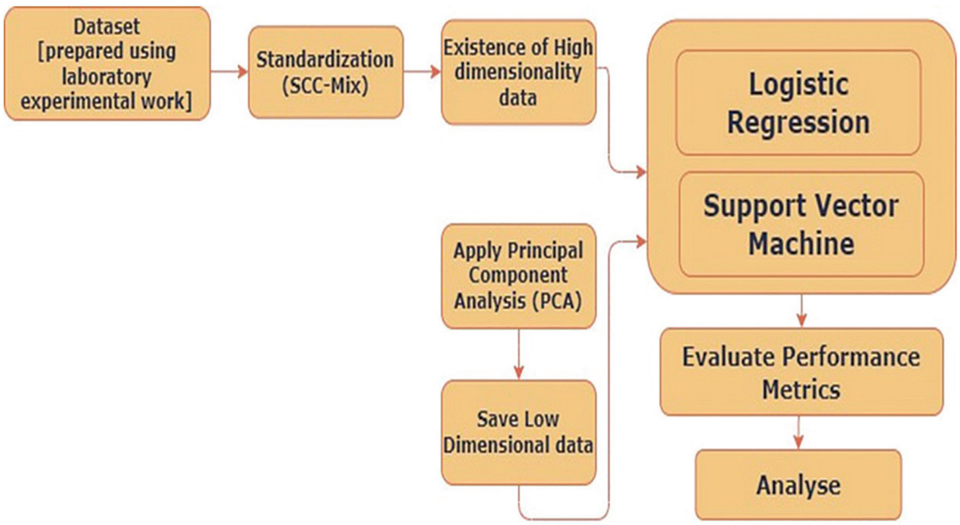

Figure 2: Proposed Architecture.

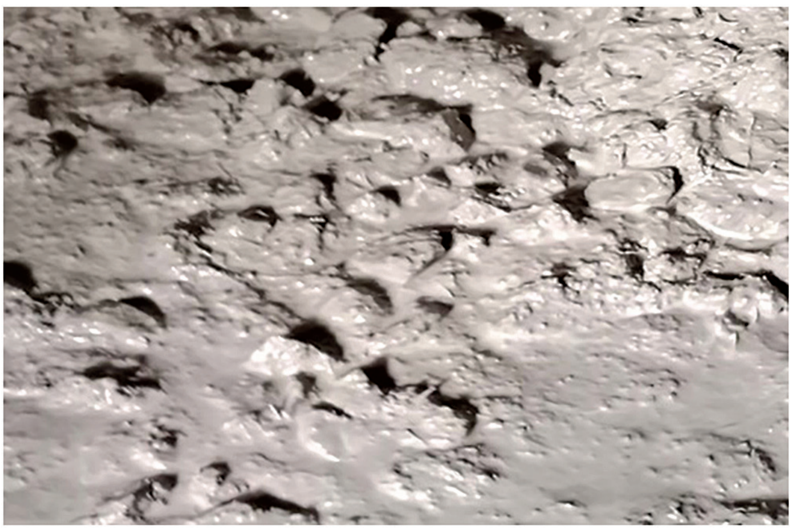

Figure 3: Self Compacting Concrete Mix.

Table 1: Mix Proportions of Fiber Reinforced Self Compacting Concrete.

MIX ID	CEMENT (kg/m^3)	FLY ASH (kg/m^3)	FIBER (kg/m^3)	FINE AGGREGATE (kg/m^3)	COARSE AGGREGATE (kg/m^3)	WATER (LITRES)	SP (LITRES)
SCC_FA00_KF0.0	480	0	0	956	766	173	4.32
SCC_FA00_KF0.1	480	0	1.21	956	766	173	4.32
SCC_FA00_KF0.2	480	0	2.42	956	766	173	4.32
SCC_FA00_KF0.3	480	0	3.63	956	766	173	4.32
SCC_FA00_KF0.4	480	0	4.84	956	766	173	4.32
SCC_FA10_KF0.0	432.5	47.5	0	956	766	170	4.23
SCC_FA10_KF0.1	432.5	47.5	1.21	956	766	170	4.23
SCC_FA10_KF0.2	432.5	47.5	2.42	956	766	170	4.23
SCC_FA10_KF0.3	432.5	47.5	3.63	956	766	170	4.23
SCC_FA10_KF0.4	432.5	47.5	4.84	956	766	170	4.23
SCC_FA15_KF0.0	408.5	71.5	0	956	766	169.5	4.14
SCC_FA15_KF0.1	408.5	71.5	1.21	956	766	169.5	4.14
SCC_FA15_KF0.2	408.5	71.5	2.42	956	766	169.5	4.14
SCC_FA15_KF0.3	408.5	71.5	3.63	956	766	169.5	4.14
SCC_FA15_KF0.4	408.5	71.5	4.84	956	766	169.5	4.14
SCC_FA20_KF0.0	385	95	0	956	766	168	4.05
SCC_FA20_KF0.1	385	95	1.21	956	766	168	4.05
SCC_FA20_KF0.2	385	95	2.42	956	766	168	4.05
SCC_FA20_KF0.3	385	95	3.63	956	766	168	4.05
SCC_FA20_KF0.4	385	95	4.84	956	766	168	4.05
SCC_FA25_KF0.0	360.5	119.5	0	956	766	166.5	3.96
SCC_FA25_KF0.1	360.5	119.5	1.21	956	766	166.5	3.96
SCC_FA25_KF1.2	360.5	119.5	2.42	956	766	166.5	3.96
SCC_FA25_KF0.3	360.5	119.5	3.63	956	766	166.5	3.96
SCC_FA25_KF0.4	360.5	119.5	4.84	956	766	166.5	3.96
SCC_FA30_KF0.0	337	143	0	956	766	165	3.87
SCC_FA30_KF0.1	337	143	1.21	956	766	165	3.87
SCC_FA30_KF0.2	337	143	2.42	956	766	165	3.87
SCC_FA30_KF0.3	337	143	3.63	956	766	165	3.87
SCC_FA30_KF0.4	337	143	4.84	956	766	165	3.87

4.2. Workability properties of SCC

The self-compaction is achieved based on the fresh concrete properties. To attain self-compaction, the given fresh concrete mix should satisfy the three essential properties: flowability (filling ability), passing ability (passing between the reinforcement), and stability (segregation resistance). Each property devices a different testing procedure and testing methods. In this research work, the slump flow test is chosen for measuring the flowability of the concrete, V-funnel test is selected to measure the filling ability and segregation resistance of the concrete, and the L-box test is conducted to measure the passing ability of the concrete between the reinforcements. The maximum size of the aggregate used in the concrete is limited to 20 mm in all the tests.

The test results are converted into binary values, such as 0 and 1, for modeling in the machine learning algorithm. The conversion of the binary value is based on the EFNARC and IS 456–2000 guidelines. Table 3 indicates the EFNARC and IS 456-2000 guidelines. Table 2 represents the binary values of the Workability Parameters of FRSCC.

Table 2: Workability Parameters of FRSCC.

MIX ID	SLUMP	V-FUNNEL	L-BOX
SCC_FA00_KF0.0	1	1	1
SCC_FA00_KF0.1	1	1	1
SCC_FA00_KF0.2	1	0	0
SCC_FA00_KF0.3	0	0	0
SCC_FA00_KF0.4	0	0	0
SCC_FA10_KF0.0	1	1	1
SCC_FA10_KF0.1	1	1	1
SCC_FA10_KF0.2	1	1	0
SCC_FA10_KF0.3	1	0	0
SCC_FA10_KF0.4	0	0	0
SCC_FA15_KF0.0	1	1	1
SCC_FA15_KF0.1	1	1	1
SCC_FA15_KF0.2	1	1	1
SCC_FA15_KF0.3	1	0	0
SCC_FA15_KF0.4	1	0	0
SCC_FA20_KF0.0	1	1	1
SCC_FA20_KF0.1	1	1	1
SCC_FA20_KF0.2	1	1	1
SCC_FA20_KF0.3	1	1	0
SCC_FA20_KF0.4	1	0	0
SCC_FA25_KF0.0	1	1	1
SCC_FA25_KF0.1	1	1	1
SCC_FA25_KF1.2	1	1	1
SCC_FA25_KF0.3	1	1	1
SCC_FA25_KF0.4	1	1	0
SCC_FA30_KF0.0	1	1	1
SCC_FA30_KF0.1	1	1	1
SCC_FA30_KF0.2	1	1	1
SCC_FA30_KF0.3	1	1	1
SCC_FA30_KF0.4	1	1	1

Table 3: Workability Guidelines of SCC.

CLASSIFICATION	1	0
Slump Flow	650 mm – 800 mm	Other than 650 mm – 800 mm
V-Funnel	6 sec – 12 sec	Other than 6 sec – 12 sec
L-Box	0.8 ratio – 1.0 ratio	Other than 0.8 – 1.0 ratio

4.3. Standardization

The first step in machine learning modeling is standardization. The standardization technique is an important tool that needs consider in logistic regression or any machine learning algorithm. The input parameters of the hypothesis have various ranges of scales and units which leads to bias in the output. For example, cement range from 337–480 kg/m^3 which is more than the fiber range 0–4.84 kg/m^3 or in some cases some input features are in kg/m^3 and some features in percentage. So, to avoid misclassification, this standardization technique is used. The standardization technique is used in the input features of the SCC mix. This feature scaling is an essential

Table 4: Standardized Mix Proportions of FRSCC.

MIX ID	CEMENT (kg/m^3)	FLY ASH (kg/m^3)	FIBER (kg/m^3)	FINE AGGREGATE (kg/m^3)	COARSE AGGREGATE (kg/m^3)	WATER (LITRES)	SP (LITRES)
SCC_FA00_KF0.0	1.688	–1.688	–1.414	0.000	0.000	1.681	1.463
SCC_FA00_KF0.1	1.688	–1.688	–0.707	0.000	0.000	1.681	1.463
SCC_FA00_KF0.2	1.688	–1.688	0.000	0.000	0.000	1.681	1.463
SCC_FA00_KF0.3	1.688	–1.688	0.707	0.000	0.000	1.681	1.463
SCC_FA00_KF0.4	1.688	–1.688	1.414	0.000	0.000	1.681	1.463
SCC_FA10_KF0.0	0.678	–0.678	–1.414	0.000	0.000	0.517	0.878
SCC_FA10_KF0.1	0.678	–0.678	–0.707	0.000	0.000	0.517	0.878
SCC_FA10_KF0.2	0.678	–0.678	0.000	0.000	0.000	0.517	0.878
SCC_FA10_KF0.3	0.678	–0.678	0.707	0.000	0.000	0.517	0.878
SCC_FA10_KF0.4	0.678	–0.678	1.414	0.000	0.000	0.517	0.878
SCC_FA15_KF0.0	0.168	–0.168	–1.414	0.000	0.000	0.323	0.292
SCC_FA15_KF0.1	0.168	–0.168	–0.707	0.000	0.000	0.323	0.292
SCC_FA15_KF0.2	0.168	–0.168	0.000	0.000	0.000	0.323	0.292
SCC_FA15_KF0.3	0.168	–0.168	0.707	0.000	0.000	0.323	0.292
SCC_FA15_KF0.4	0.168	–0.168	1.414	0.000	0.000	0.323	0.292
SCC_FA20_KF0.0	–0.331	0.331	–1.414	0.000	0.000	–0.258	–0.292
SCC_FA20_KF0.1	–0.331	0.331	–0.707	0.000	0.000	–0.258	–0.292
SCC_FA20_KF0.2	–0.331	0.331	0.000	0.000	0.000	–0.258	–0.292
SCC_FA20_KF0.3	–0.331	0.331	0.707	0.000	0.000	–0.258	–0.292
SCC_FA20_KF0.4	–0.331	0.331	1.414	0.000	0.000	–0.258	–0.292
SCC_FA25_KF0.0	–0.851	0.851	–1.414	0.000	0.000	–0.840	–0.878
SCC_FA25_KF0.1	–0.851	0.851	–0.707	0.000	0.000	–0.840	–0.878
SCC_FA25_KF1.2	–0.851	0.851	0.000	0.000	0.000	–0.840	–0.878
SCC_FA25_KF0.3	–0.851	0.851	0.707	0.000	0.000	–0.840	–0.878
SCC_FA25_KF0.4	–0.851	0.851	1.414	0.000	0.000	–0.840	–0.878
SCC_FA30_KF0.0	–1.351	1.351	–1.414	0.000	0.000	–1.423	–1.463
SCC_FA30_KF0.1	–1.351	1.351	–0.707	0.000	0.000	–1.423	–1.463
SCC_FA30_KF0.2	–1.351	1.351	0.000	0.000	0.000	–1.423	–1.463
SCC_FA30_KF0.3	–1.351	1.351	0.707	0.000	0.000	–1.423	–1.463
SCC_FA30_KF0.4	–1.351	1.351	1.414	0.000	0.000	–1.423	–1.463

process in modeling. In this case, the input features (X) are materials used. These features need a scaling process, the standardization is done by the statistical equation is known as Z-score normalization and the standardized mix proportions of FRSCC is presented in Table 4.

$$X\_New = \frac{X\text{-}Mean}{Standard\ Deviation} \tag{1}$$

4.4. Principal component analysis (PCA)

In general, real-time data are purely highly dimensional in nature. So, processing those data is a very much complex task. Hence current research recommends a Principal Component Analysis (PCA) approach to converting high-dimensional to low-dimensional data [31]. There are seven input features in each mix, truly it is not requiring all the features in training the model. In the mix design, the aggregates are kept constant. So, in the standardization process, both are zero. The remaining features are Cement, Fly Ash, Kenaf Fiber, Water and

Super Plasticizer. It is very difficult to make the model hypothesis correlate all five features with targets. So, that PCA analysis is done. The PCA for two components is illustrated in Figure 4.

Let's consider the above Table 5, X1 and X2 values are the given data point which is the normal (X1, X2) coordinate.

Step 1: To calculate the mean value of both X1, X2

$$\overline{X1} = \frac{\sum_{i=0}^{n} g(X1)}{m} \tag{2}$$

$$\overline{X2} = \frac{\sum_{i=0}^{n} g(X2)}{m} \tag{3}$$

Using Equations 2 and 3, the mean value of both X1 and X2 is determined, which is $\overline{X1} = -0.10377$ and $\overline{X2} = 0.10377$ respectively.

Step 2: Data adjusting

To make all the data points pass through the origin, subtracted every data point X1 and X2 to their respective mean value. This process is said to be Data Adjust. the results of the data adjustment will be in Table 6.

The average of the results of data adjustments is zero. From the data adjustment process, clearly understand that without applying the data adjustment process, the data point did not pass through the origin. If plot the original data point in the graph, it means it deviates from the origin. Hence, a data adjustment process is required in principle component analysis.

Step 3: Determine the Covariance matrix

It is the estimation between the two dimensions. Utilizing determining covariance matrix, we determine how variables X1 and X2 vary together.

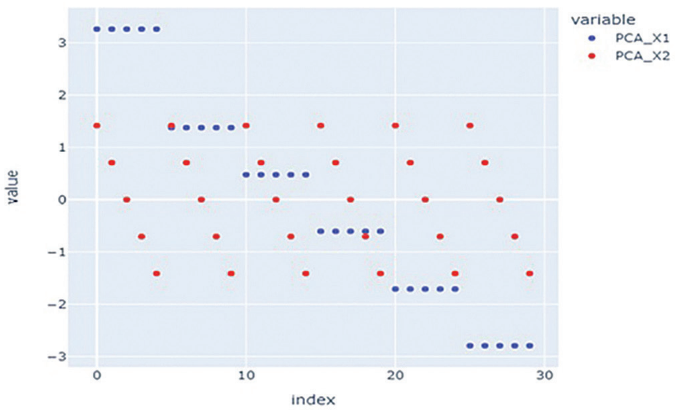

Figure 4: Principal Component Analysis for Input Mix Proportions.

Table 5: Input Data.

X1	1.688	1.688	0.678	0.678	0.168	0.168	–0.331	–0.331	–0.851	–0.851	–1.351	–1.351	–1.351
X2	–1.688	–1.688	–0.678	–0.678	–0.168	–0.168	0.331	0.331	0.851	0.851	1.351	1.351	1.351

Table 6: Output After the Process of Data Adjustment.

X1	–1.792	–1.792	–0.782	–0.782	–0.272	–0.272	0.227	0.227	0.747	0.747	1.247	1.247	1.247
X2	1.792	1.792	0.782	0.782	0.272	0.272	–0.227	–0.227	–0.747	–0.747	–1.247	–1.247	–1.247

$$Cov(X1, X2) = \frac{\sum_{i=0}^{n} (X1 - \overline{X1})\ (X2 - \overline{X2})}{n-1} \tag{4}$$

X1 – Original x-axis data point.

$\overline{X}$ – The mean of X.

X2 – Original y-axis data point.

$\overline{X2}$ – The mean of Y.

N – Total sample.

Note: Positive value implies that, if our output is positive, then its direction would be the same. For instance, the X1 value increases corresponding X2 value also increases.

Step 4: Covariance Matrix

The covariance is (X1,X1) & (X2,X2) are 1.140 and (X1,X2) & (X2,X1) are 0.000. These elements present in non-diagonals in this covariance matrix are positive. Also expect both X1 and X2 values are increases together.

Step 5: Determine Eigen value and Eigen vector for the covariance matrix

Eigenvector represents the projected vector of the data. It is directed perpendicularly towards the data and the new direction determines the most important data which lies in the following values for the given example,

$$Eigen\ value = \begin{pmatrix} 1.140 \\ 1.140 \end{pmatrix}\ Eigen\ vectors = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}$$

Step 6: To determine PCA value

The highest Eigenvalue with the corresponding Eigenvector will be selected as PCA, then the rest of the dimension is ignored.

1. Take 'n' dimension data (here n = 2), so need to find 'n' Eigenvector.
2. Then Eigenvector 'P' can be selected. Also, p < n and need to reduce the original dimension.

So, the entire re-represent data are determined using the given formula. Also, the data taken here is data adjustment output.

Resultant vector = Row feature vector * Row data adjust

4.5. Logistic regression

Logistic Regression (LR) is a powerful classifier found among supervised machine-learning algorithms [32]. It is an extension of the generic regression modeling that, when imposed on a dataset, reflects the probability of a given instance occurring or not occurring [33]. Since it is probability-based, the outcome of the model will fall somewhere between 0 and 1 and LR determines the likelihood of a new observation falling into a particular category. As a consequence of this, a threshold is chosen and applied, which specifies the break between the two classes so that the LR can be implemented as a binary classification. For example, a probability value that has been determined as being greater than 0.5 is referred to as belonging to "class A," while anything lower than that value belongs to "class B." The LR model can be generalized as a multinomial logistic regression [34], which allows for the modeling of categorical variables that have more than two possible values (Figure 5).

Initially, LR analyses the instance of the given dataset and fits the logistic model over the data point by using a function such as $\frac{1}{1 + e^{-z}}$ an error has been minimized with help of the cost function.

$$\text{In} \left[\frac{P(Z)}{1 - P(z)} \right] = b_0 + b_1A_1 + b_2A_2 + \ldots + b_nA_n \tag{5}$$

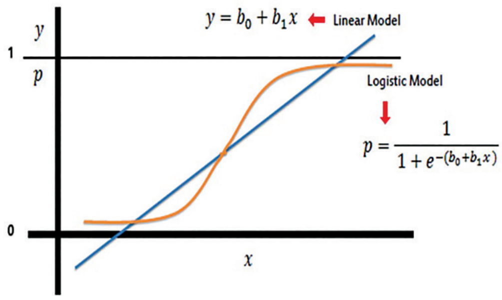

Figure 5: Logistic Regression Model.

$$\frac{P(z)}{1-P(z)} = e^{b_0 + b_1A_1 + b_2A_2 + \ldots + b_nA_n} \tag{6}$$

$$P(Z) = e^{b_0 + b_1A_1 + \ldots + b_nA_n} - P(Y)e^{b_0 + b_1A_1 + \ldots + b_nA_n} \tag{7}$$

$$P(z) = \frac{e^{b_0 + b_1A_1 + \ldots + b_nA_n}}{1 + e^{b_0 + b_1X_1 + \ldots + b_nX_n}} \tag{8}$$

The LR model establishes a direct relationship between the likelihood of Y and the predictor variables through the use of Equation 8. Estimating the values of the $n + 1$ uncertain variables in the equation is the purpose of LR. The likelihood ratio compares the likelihood of success against the likelihood of failure and minimizes the error. The logistic transformation guarantees that predicted values do not exceed the range of 0 to 1 and prevent such values from falling outside of the range [35].

$$Probability\ (Event) = \frac{odds(event)}{1 + odds(event)} \tag{9}$$

4.6. Support vector machine (SVM)

SVM is a classification method that optimizes the use of marginal planes. In its most basic form, the SVM is a binary linear classifier [36, 37]. But it can also analyze non-linear data with the help of Kernels and multi-class data with the help of a variety of approaches. In addition to this, it divides the classes according to the dimensions of the space (also known as the ideal margin) between both borderline occurrences (called Support Vectors). Because of this, some refer to it as the optimal margin classifier. SVM has been adapted to deal with multi-class issues by utilizing methods like One-Against-One [38], One-Against-Rest [39], and Acyclic Directed Graph SVM [40], amongst others.

4.6.1. Linear SVM

The Linear SVM technique has seen an extensive application for classification and prediction [20]. This method is founded on a collection of very effective learning strategies that implement the statistical learning model [20]. Initially, support vector machines (SVMs) were developed to address binary classification. They are capable of working on problems involving the classification of multiple classes by integrating multiple binary SVM classifiers for every pair of categories. In addition, SVM can be modified to function as a nonlinear classifier by making use of nonlinear kernels in the training process. The simplest version of the support vector machine, which identifies an input vector $y\ R_n$, is defined as follows:

$$g(y) = \omega\phi(y) + c \tag{10}$$

$$\min_{\omega, a, \xi_i} \frac{1}{2} \parallel \omega \parallel^2 + D\frac{1}{N}\sum_{j=1}^{M} \xi_j \tag{11}$$

Subject to the following constraints,

$$Z_i\ \left(\omega.\phi(y_j) + c_j\right)\ \leq\ 1 - \xi_j \tag{12}$$

$$\xi \geq 1, \text{ for } j = 1, \ldots, M \tag{13}$$

where 'c' and 'a' are two variables that need to be estimated based on their respective inputs. The symbol (y) represents the non-linear convolution layer in the feature space. Unlike other classifiers, the Support Vector Machine (SVM) finds a negotiated compromise between providing a basis corresponding to generalisation and the empirical error by minimising systemic risk rather than by minimising empirical error in the training dataset [41].

4.6.2. Non-linear SVM classification

In many scenarios, effective predictive results cannot be obtained utilizing linear SVM because the data cannot be separated linearly. It is necessary to convert the input data into a space with a higher dimension., where it can be linearly separated, by the use of an appropriate mapping function (a kernel function). Consequently, a hyperplane can be used to partition data even in significantly greater spaces. Figure 6. shows how a nonlinear kernel functional, like a Radial Basis Kernel, can transform data that is not differentiable in two dimensions into data that is manageable in the nonlinear feature set.

One possible expression for a non-linear SVM in generality is:

$$g(x) = \sum_{i=1}^{M} \alpha_i x_i \ \mathrm{P}(y_i, y_j) + c \tag{14}$$

In addition, the Lagrangian optimization problem is altered for a generalized non-linear support vector machine by the substitution y_i of with a mapping function $\mathrm{P}(y_i, y_j)$ that is responsible for the non-linear mapping together into a feature set, as seen in the following expression:

$$L\left((\alpha) = max\sum_{j=1}^{M} \alpha_j - \frac{1}{2}\sum_{j=1}^{M}\sum_{i=1}^{M} \alpha_i \alpha_j x_i x_j p(y_i, y_j)\right) \tag{15}$$

$$\text{subject to} \begin{cases} \text{Single linear equality constraint} & \sum_{j=1}^{M} \alpha_j x_i = 0 \\ \text{and the inequality constraint} & 0 \le \alpha_h \le D \end{cases} \tag{16}$$

The following is an expression that may be used to describe a generic decision boundary for non-linear SVM. This function is utilized for constructing the best possible hyperplane that separates the feature space.

$$g(x) = \left(\sum_{j=1}^{M} \alpha_i x_i \ \mathrm{P}(yi, y) + c\right) \tag{17}$$

4.6.3. Different kinds of kernel function for non-linear SVM

One type of data-independent algorithm is the kernel approach. The inner components of a subspace are analyzed using the kernel function. To clarify, a kernel-based approach consisted of a component that carries out the mappings into the feature set, and then a trained model is used in the feature set to unearth the linear patterns therein. Within the fields of statistics study and machine learning, this technique has long since been standard practice. By applying a computational shortcut known as the kernel function, one can easily express the linear patterns in high-dimensional spaces. Its primary benefit is that it allows the user to create a non-linear boundary by employing techniques originally developed for linear classifiers. For another, it enables the use of a classifier that does not naturally map onto a finite-dimensional vector space.

4.6.3.1. Linear kernel

The linear kernel is shown by the kernel function of x and y, which is written as:

$$\mathrm{K}(y_i, y_j) = y_i \cdot y_j.$$

This expression is used to measure how non-linear the training dataset is also a benchmark for the final improved performance in categorization when non-linear kernels are being used.

4.6.3.2. Polynomial kernel

Polynomial mapping is a generic process for sculpting that does not follow a straight line. This is done with the following term:

$$\mathrm{p}\,(y_i, y_j) = \left(1 + (y_i \cdot y_j)\right)^t \tag{18}$$

where ‘t’ is a factor that the user can set. One problem with this technique is that it can give rise to overfitting because using a polynomial degree makes the classification texture more complicated.

4.6.3.3. Sigmoid kernel

A hyperbolic tangent feature in the contour of a sigmoid is used in neural networks. In SVM classification, a sigmoidal kernel could also be used, which is written as follows:

$$\mathrm{p}\,(y_i, y_j) = \tan\left\{\gamma(y_i \cdot y_j) + c\right\} \tag{19}$$

4.6.3.4. Radial basis function kernel

To construct the Gaussian Radial Basis Function (RBF) Kernel is:

$$\mathrm{p}\,(y_i, y_j) = \exp\left(\frac{-\| y_i - x_j \|^2}{2\sigma^2}\right) \tag{20}$$

Exponential RBF could be used if the way the hyper-plane regions are defined is not consistent. refers to how skewed the dispersion is, and it is a parameter that the user can change.

5. RESULT AND DISCUSSION

The experimentation carried out to develop FRSCC is examined in this section. The proposed model encompasses the machine learning approach such as principal component analysis and logistic regression. The dataset has been created based on the various laboratory workability tests which have given in Tables 1 and 2. So far, no research work carried forward to predict the workability of the SCC using machine learning approaches. Hence our research work is concerned with the development of SCC workability parameters. Our proposed work utilizes two classification algorithms for effectively categorizing the self-compacting concrete including SVM and LR. Also, performance evaluation metrics such as accuracy, precision, recall, sensitivity, specificity, F1-score and ROC curve has been determined for both the classification algorithms and comparison have been made. From the comparison, Logistic Regression produces a more reliable outcome than support vector machine.

The confusion matrix is used to assess the classification model’s performance by using Python Programming with different random state conditions. A two-dimensional matrix with predicted and actual values is called a confusion matrix. The value from the specified target in the workability test is the actual value. The predicted value is the mix’s feasibility as ascertained by applying the hypothesis. Since this is a classification hypothesis, the model’s performance is evaluated using this confusion matrix as a basis. In addition to predicting accuracy, the confusion matrix also identifies the kind of error that occurs in the model. There are four cases in the confusion matrix True Positive (TP), True Negative (TN), False Positive (FP), and False Negative (FN).

The testing data sets consist of a total of six targets. The model selects the six random targets with their corresponding mix proportions for the hypothesis testing. The confusion matrix for the logistic regression slump flow test is given in Figure 6. From the confusion matrix for the slump flow test, the TP is five, TN is one and both FP & FN is zero. So, the Type I and Type II errors in the hypothesis are zero. Therefore, the accuracy of the model is 100%. Also, the following equations represent the formulas for the evaluation metrics that are used in the present work.

$$Accuracy = \frac{\sum TP, TN}{\sum TP, TN, FP, FN} \tag{21}$$

$$Specifity = \frac{TN}{\sum TN, FP} \tag{22}$$

$$Sensitivity = \frac{TP}{\sum FP, FN} \tag{23}$$

$$Precision = \frac{TP}{\sum TP, FP} \tag{24}$$

$$Recall = \frac{TP}{\sum TP, FN} \tag{25}$$

$$F1 - Score = \frac{TP}{TP + \frac{1}{2}\{\sum TP, FN\}} \tag{26}$$

The confusion matrix for the logistic regression V-Funnel test is given in Figure 7. From the confusion matrix for the V-Funnel, the TP is four, TN is one but the FP is one. The target is zero, the model predicted the target as one. So, it is a Type I error. Therefore, the accuracy of the model is reduced in the testing data set. The accuracy of the model is 83.33% for the V-Funnel test.

The confusion matrix for the logistic regression L-Box test is given in Figure 8. From the confusion matrix for the L-Box, the TP is three, TN is two but the FN is one. The target is one, the model predicted the target as zero. So, it is a Type II error. Therefore, the accuracy of the model is reduced in the testing data set. The accuracy of the model is 83.33% for the L-Box test also.

A graph known as a Receiver Operating Characteristic curve (ROC curve) shows the classifier's accuracy when using all available modelling tools. Plotting the true positive rate (TPR) against the false positive rate (FPR) at different threshold values yields the ROC curve.

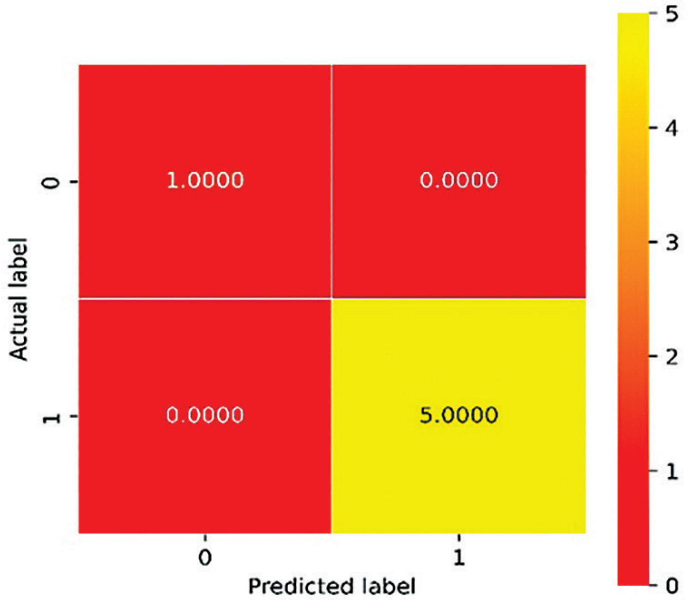

Figure 6: Confusion Matrix for the Slump Flow.

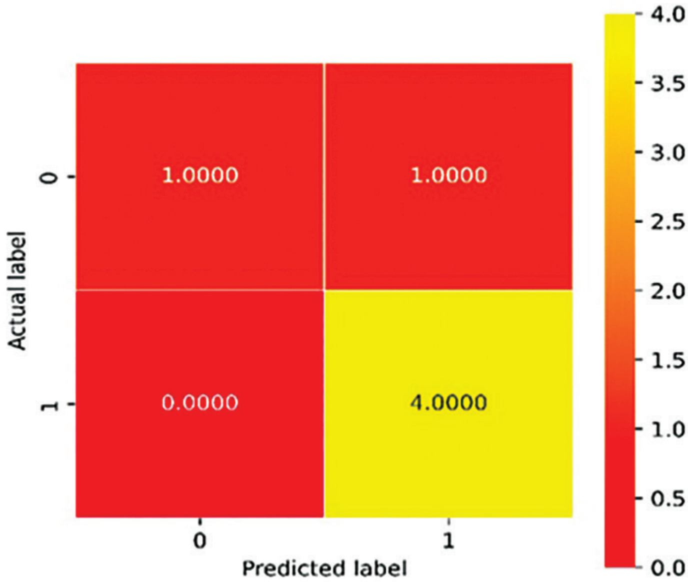

Figure 7: Confusion Matrix for the V-Funnel.

The True Positive Rate (FPR) is given by the relation

$$TPR = \frac{TP}{TP + FN}$$

The False Positive Rate (FPR) is given by the relation

$$FPR = \frac{FP}{TN + FP}$$

Figure 9. displays the ROC curve for the slump flow model. The TPR vs. FPR of Slump Flow is used to plot it. Given that the slump model's Area Under the Curve (AUC) is 1.0, the model's accuracy is 100%.

Figure 10. displays the ROC curve for the V-funnel model. The V-Funnel's TPR vs. FPR is used to plot it. Given that the V-funnel model's Area Under the Curve (AUC) is only 0.75, the model's accuracy is 75%.

Figure 11. displays the L-box model's ROC curve. Plotting is done using the L-Box TPR vs. FPR. Since the Area Under the Curve (AUC) for the L-box model is 0.87, the model's accuracy is 87%.

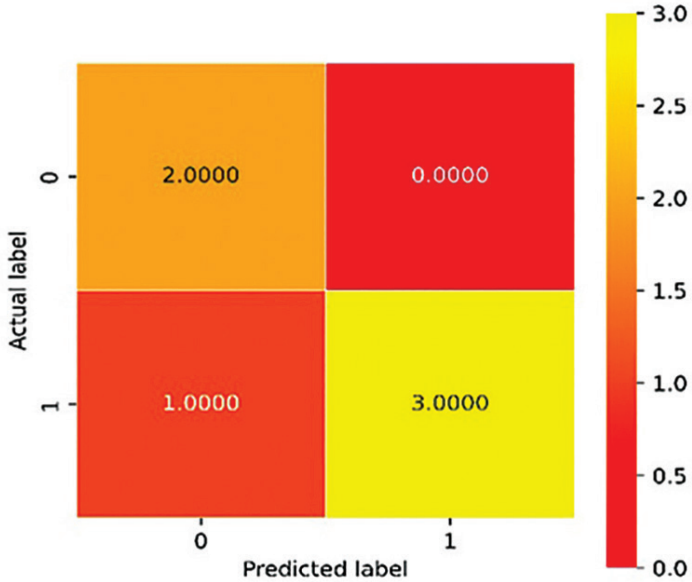

Figure 8: Confusion Matrix for the L-Box.

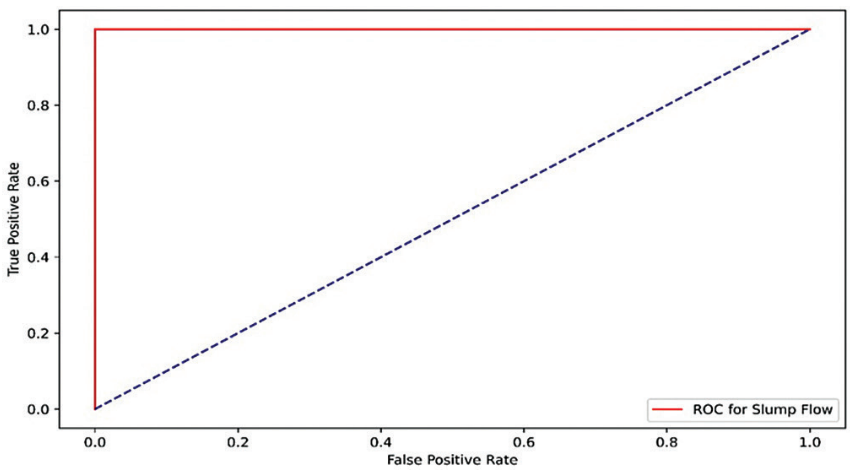

Figure 9: ROC Curve for the Slump Flow.

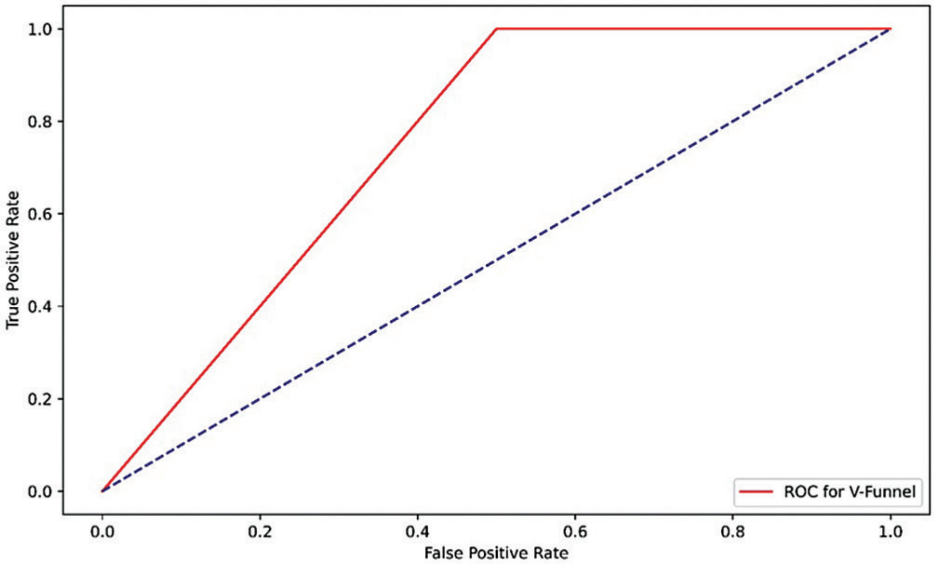

Figure 10: ROC Curve for the V-Funnel.

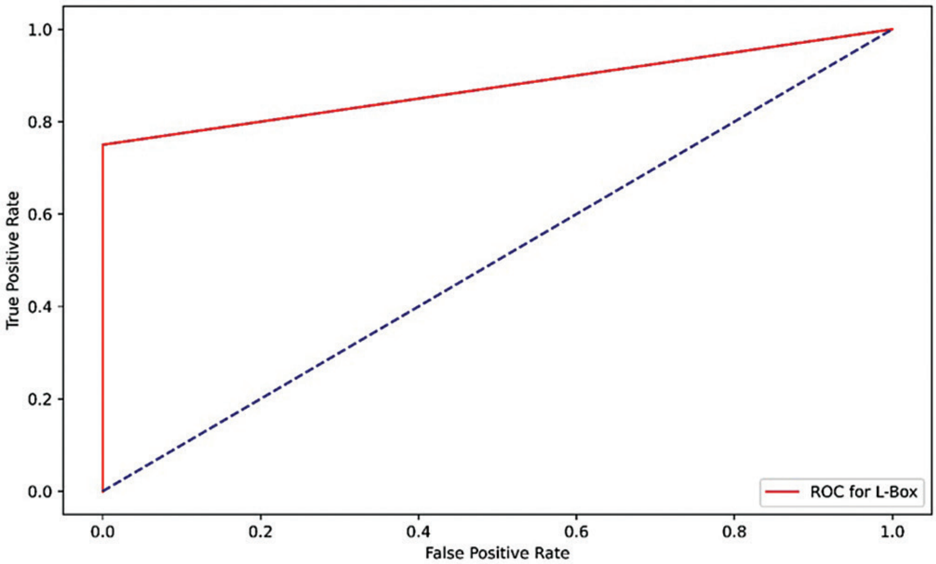

Figure 11: ROC Curve for the L-Box.

Table 7: Comparison of Performance between Support Vector Machine (SVM) and Logistic Regression without Principal Component Analysis.

PERFORMANCE EVALUATION METRICS USED	SUPPORT VECTOR MACHINE (SVM)	LOGISTIC REGRESSION (LR)
Accuracy	93.76	95.32
Precision	94.32	95.93
Recall	93.82	94.21
Sensitivity	92.21	95.01
Specificity	93.01	95.49
F1-score	92.29	95.29

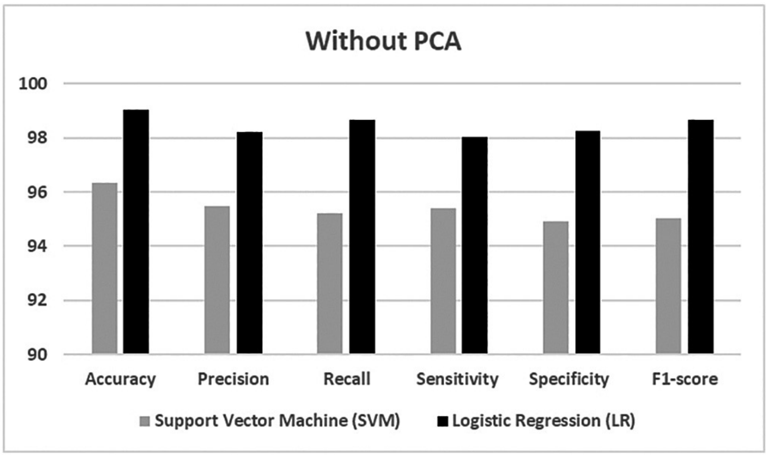

Figure 12: Comparison of Performance of SVM and Logistic Regression without PCA.

Table 8: Comparison of Performance between Support Vector Machine (SVM) and Logistic Regression with Principal Component Analysis.

PERFORMANCE EVALUATION METRICS USED	SUPPORT VECTOR MACHINE (SVM)	LOGISTIC REGRESSION (LR)
Accuracy	96.32	99.03
Precision	95.49	98.21
Recall	95.21	98.66
Sensitivity	95.39	98.01
Specificity	94.93	98.25
F1-score	95.01	98.65

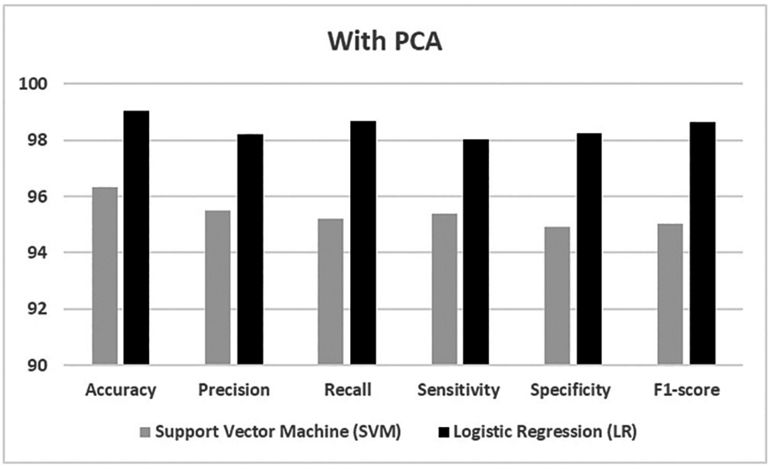

Figure 13: Comparison of Performance of SVM and Logistic Regression with PCA.

Table 7 explores the working performance of the SVM and LR without PCA. From the comparison, we can find that logistic regression performs well with an accuracy of 95.32%, which is a comparably good outcome to support vector machine. It can be given in a visualized way in Figure 12. Followed by this, Table 8 explores the working performance of the SVM and LR with PCA. From the comparison, we can find that logistic regression performs well with an accuracy of 98.32%, which is a comparably good outcome to support vector machine. It can be given in a visualized way in Figure 13 The performance of the classification outcomes is gradually increased once PCA is applied. From that, we infer this dataset required dimensionality reduction approaches to produce a reliable outcome.

6. CONCLUSION

In this research work, the Fiber Reinforced Self Compaction Concrete (FRSCC) workability attributes were categorized using machine learning-based modeling. This classification can be used to forecast the optimal Self Compaction Concrete (SCC) mix as well as whether the supplied mix of fiber reinforced concrete satisfies the self-compaction requirement or not. There are thirty data sets were used in the modeling for Slump flow, V-Funnel, and L-Box with different mix proportions. The modeling is based on the Logistic Regression (LR) and Support Vector Machine (SVM) approach of binary classification without and with Principal Component Analysis (PCA). The performance of LR is more than 5-10% when compared to SVM. The confusion matrix and ROC curve were used to predict the performance of the Logistic Regression model. For the slump flow model, the accuracy of the prediction is more when compared to the training. It shows that the ML-based modeling predicts the FRSCC performance well with given input mix proportions. For V-Funnel and L-Box the accuracy of the prediction is similar to the training and it has Type I and Type II errors and these errors are minimized using more data sets in the training. It will be optimized by the more input data sets. From the research, the performance of Logistic Regression modeling is more efficient for the prediction of FRSCC workability properties than SVM. More trials and material wastages were reduced by using the Logistic Regression modeling. The optimized Self Compaction Concrete (SCC) mix can be produced using Logistic Regression with Principal Component Analysis (PCA). This model is a very effective and less time-consuming process. The model can be exported and utilized in Ready-Mix Concrete plants for Fiber Reinforced Self-Compaction Concrete (FRSCC) production.

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