Prediction of the Fresh Performance of Steel Fiber Reinforced Self-Compacting Concrete Using Quadratic SVM and Weighted KNN Models

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\textbf{ABSTRACT} Steel fiber reinforced self-compacting concrete (SFRSCC) is a special type of concrete that is widely researched in literature due to its superior properties. As it is difficult to provide its high workability qualities, SFRSCC is thought to be in need of an economic and quick design process. In this study, it is aimed to predict the fresh properties of SFRSCC mixtures following with the standards at the preliminary design stage. With this aim, two different classification methods were applied successfully to a comprehensive dataset collected from international publications. The models used to classify the fresh performance of SFRSCC were Weighted K-Nearest Neighbors (W-KNN) and Quadratic Support Vector Machine (Q-SVM). Consequently, acceptable success rates were obtained from the models. For the prediction of slump-flow, the accuracy values were 0.76 and 0.84 for the W-KNN and Q-SVM models, respectively. For the V-funnel time, the accuracy values were 0.90 and 0.92 for the W-KNN and Q-SVM models, respectively. Owing to the recommended methods, it is expected to reduce the number of trial mixtures in the preliminary design stage of SFRSCC.

\textbf{INDEX TERMS} Fresh properties, self-compacting concrete, steel fiber, quadratic support vector machine, weighted k-nearest neighbor.

\section{I. INTRODUCTION}

The normal (traditional) concrete has many advantages and limitations. The concrete that is obtained by improving the fresh and hardened performance of the normal concrete or by turning the limitations into an advantage is named as special concrete. One of the most well-known and most widely used concrete types in the industry is self-compacting concrete (SCC) \cite{1}. Fresh concrete performance is the indispensable property that provides widespread use of SCC. As it passes among the rebars with its weight and settles into the mold without applying any vibration, it provides excellent advantages to SCC \cite{2}.

Steel fiber is added to SCC to improve the performance of hardened concrete \cite{3}. The optimum amount of steel fiber in concrete ensures maximum flexural strength. However, the added steel fibers negatively affect the performance of fresh concrete. As the amount of steel fiber increases, the workability of Steel fiber reinforced self-compacting concrete (SFRSCC) decreases. The SFRSCC must have proper mixture ratios for high performance of fresh concrete \cite{4}.

Mixture ratios of SCC should provide the basic requirements of concrete such as filling ability, passing ability, and segregation resistance \cite{2}. For this purpose, many researchers performed studies on the optimum mix design of SCC. The first study on this fact is based on empirical design method by Okamura and Ozawa \cite{5}, \cite{6}. Later, compressive strength model \cite{7}, aggregate packing method \cite{8}, statistical factorial model \cite{9} and rheology of paste model \cite{10}, have been proposed for mixture design method of SCC \cite{11}. In addition to these models, practical graphic-based models have been developed for more comfortable use in industrial applications \cite{12}.

The main reason why many different mix design methods for self-compacting concrete to be proposed is the mineral additives used in the production of SCC \cite{13}. The physical,
chemical and particle structure properties of mineral additives such as silica fume, fly ash, waste marble dust, natural stone powders, metakaolin, blast furnace slag, and rice husk ash are different from each other [12]. Consequently, when the type of mineral additives is varied, the properties of fresh concrete change in return. Accordingly, in cases where many factors affect a variable, computational methods such as intelligence system and machine learning are used to determine these effects in the literature. These methods are remarkably efficient in the solution of problems with multivariate and multiple outputs [14], [15].

When self-compacting concrete is produced using steel fibers, it is even more difficult to achieve optimum mixed design values. Since the added steel fibers have different sizes and shapes, the fresh concrete properties of SFRSCC change. Ferrara et al. proposed a method for the mix design of SFRSCC [16]. This method has a rheology of paste model-based approach. Mashhadban et al. proposed a model for estimating the mechanical properties of SFRSCC using the algorithm of particle swarm optimization and artificial neural network [17]. As a result, there is a relatively limited number of studies in the literature for optimal mix design of SFRSCC.

The classification methods aim to predict the categorical outputs in the data sets obtained by experimental methods by means of mathematical methods. The discovery of the mathematical relationship between the variables with input values and the class vector with output values is used to predict which of the previously unknown values belong to the classes determined by the experiments [18]. In classification, K-nearest neighbor (KNN) and support vector machine (SVM) algorithms are frequently used. The KNN algorithm is among the most basic and most common algorithms for classification [19], the SVM algorithm was applied in various studies, and they were chosen, for they are effective classification methods with high generalization performance as a result of these studies [20].

Classification methods have been used in different studies in civil engineering. In particular, system health management and classification methods for damage detection are used. In the study made by Omenzetter and Lautour; based on the analysis of the autoregressive coefficients, the nearest neighbor (NN) algorithm was used for systematically classify the damage [21]. The study made by Vitola et al. have been used the KNN algorithm to examine structures and assess possible damage [22]. Radhika et al. have used the SVM algorithm to detect damage to buildings by wind and tropical cyclone [23]. KNN and SVM algorithms are implemented successfully in many different areas such as health [24], indoor location detection [25], social networks [26] and image processing [27]. Classification methods have shown that they are useful in the areas where applied.

In practice, there is a need for an approach that suggests a mix design model taking into account the fresh features of SFRSCC [28]. Such an approach will be time and cost-effective due to trial mixes and minimizing the necessity for labor. This study aims to predict the fresh concrete classes of SFRSCCs with different mixing ratios. For this purpose, four different models were obtained by using two different databases. The two databases obtained from various studies in the literature were analyzed with Q-SVM and W-KNN methods separately. Satisfactory results were obtained in all analysis results. As a result, although many inputs have been used, the fresh concrete performance of SFRSCC has been achieved with high accuracy. All results of the designed models by this study have been discussed in section 6.

II. RESEARCH SIGNIFICANCE
The living beings are the source of inspiration for most of artificial intelligence and machine learning algorithms. For example, artificial neural network created similarly to nerve cells in the brain. Throughout history, people have learned and gained experience. They usually make high-accuracy decisions using their experience in matters where their experience is sufficient. Even in subjects that person does not know, person can make very good evaluations and obtain high accuracy results thanks to his general knowledge, culture, manners and experience. Nowadays, this unique feature of the human brain has been transferred to computers through artificial intelligence and machine learning systems and used in daily life.

Machines and devices that contain artificial intelligence and machine learning systems are used in many fields of daily life. There are many kinds of these applications that can be used successfully in the concrete sector. Conventional design of concrete mixed using classical methods (equations, tables and graphs) has a long process. Mixture design for SFRSCC is much more difficult and time consuming. The more number of mixture components to be determined increases, the more it becomes difficult to obtain the targeted fresh and hardened concrete properties. In fact, even when designing concrete mixes using conventional methods, the calculating technician/engineer has used something different from mathematical calculations. When designing concrete mix, it is known that all calculations are approximate. The test mixture is prepared in accordance with the design results and it is then determined how close it is to the target values. To achieve the targeted fresh and hardened concrete properties, the calculations are corrected and a retry mixture is prepared. This cycle continues until the target values are obtained.

According to the results of the trial mixtures, the technician/engineer decides which quantities he will replace the concrete mixture components with. It is known that what is used here is the technical knowledge and technical experience of the technician/engineer. Based on knowledge and experience, expert determines the materials to be changed and the rates of change. As knowledge and experience increases, so does the speed of achieving results.

Machine learning methods are imitations of human intelligence and experience. Machine learning methods are fast, accurate, wide solution space and highly efficient problem solving methods. Machine learning methods are used in processes such as predicting previously known groups of data,
clustering data, and predicting actual values. With the help of the data they analyze, these methods both continuously learn and increase their experience. In this way, they increase the speed of reaching results and accuracy rates.

Engineering problems are mostly related to data. For this reason, regression analysis is used to determine the relationship between two and more variables and to make predictions or estimations about that subject using this relationship as well. Machine learning methods offer alternative solutions to regression analysis in the solution of engineering problems. The reason for this is that machine-learning methods have many advantages over classical regression analysis methods. Additionally, the advantages of this study are listed below:

- With models designed using machine learning methods, it is possible to classify the data or estimate the actual values of the data; Classification is not possible with regression analysis.
- Machine learning methods are used in the evaluation of data that are meaningless.
- Obtaining an equation for the solution by curve fitting or other methods in many studies causes the result to remain in a limited solution space. However, with limited data, it is possible to obtain high accuracy results over a wider area owing to machine learning methods.
- By using machine-learning methods, the results can be reached very quickly by giving input values without making any calculations. Thus, instead of trying to solve complex mathematical models, machine-learning methods are used to gain from many parameters such as time, labor and cost.

Different criteria are used in the evaluation of the models designed by using machine-learning methods and the predictive performances of the models are measured with these criteria. Accuracy, Sensitivity and Specificity are used in the classification method in literature, while criteria such as r-squared, root mean square error and mean absolute error are used in regression analysis.

Experts use classification methods in order to predict pre-categorized data or standard ranges accepted by authorities. If the values to be estimated are real values, it is appropriate to use regression methods. When designing a concrete mixture, the intended results for fresh and hardened concrete are not accurate numerical values. The targeted results are a region between certain numbers. That is why this is a classification process. For example, the plastic consistency of fresh concrete represents a class (slump = 7~10 cm). Besides, the concrete strength of 20∼25 MPa represents a class (C20/25). C20/25 means that the minimum average compressive strength evaluated at 28 days is 20 MPa. Therefore, although the concrete mix design may seem like a regression analysis, it is actually a classification process.

When the concrete mix design methods are examined, there is no common or definite method. Because of that, there are many parameters affecting the mixing ratios. In fact, it is seen that a very limited number of parameters are taken into consideration when examining the existing mixture design methods. Therefore, after the calculations, a large number of trial mix tests are required. Increasing the number of trial mixtures means loss of time, labor loss, material loss and economic loss. It is possible to avoid these losses by using machine-learning methods, to consider a large number of parameters and to have high accuracy of the results.

III. DATA ACQUISITION

Essential requirements of SFRSCC are the filling ability, passing ability and segregation resistance [4]. Filling ability means that the concrete flows under its weight and fills the mold. As the friction between coarse and fine aggregates is reduced, the filling ability increases significantly. Reduction of friction can be achieved by adding water and chemical additives. However, this may lead to additional segregation. For this reason, the quantities must be determined very precisely. Additionally, sufficient paste should be provided to cover the surface area of the aggregates. As the friction value will be minimum in the optimum amount of paste, the filling ability will be quite serviceable [2]. The passing ability means that the SFRSCC mixture can easily pass through narrow spaces and among rebars and coarse aggregate can move in the paste without blocking. The passing ability depends on many parameters such as the content of the coarse aggregate, the largest grain size and the coarse aggregate interaction with the fine aggregate. Furthermore, the high viscosity of SFRSCC paste increases the passing ability [29], [30]. Segregation resistance is the homogeneous distribution of the coarse aggregate in the paste and during the flow of the concrete. By limiting the size and content of the coarse aggregate, adjusting the amount of mineral additive and water content in an appropriate ratio, segregation can be prevented [12].

The three essential requirements; filling ability, passing ability, and segregation resistance, for the fresh concrete properties of the SFRSCC are highly correlated [9], [31]. Several tests have been developed to identify these features. Slump-flow and v-funnel tests are the most commonly used tests. These tests are carried out mostly in consistent with EFNARC (2005) [32].

The slump-flow test is a test method that can be used both on site and in the laboratory to measure the filling ability, viscosity and segregation resistance of SFRSCC. V-funnel is used to determine both the filling ability and viscosity of SFRSCC. With the results of slump-flow and v-funnel tests, it can be determined with high accuracy whether a fresh concrete has properties of SFRSCC [1], [29]. Therefore, in this study, these two fresh concrete experiments were selected as output in the analysis.

The inputs that affect these three critical parameters for SFRSCC mixtures are mineral additives, chemical additives, and steel fiber [14], [33]. As the amounts and types of these materials change, the fresh properties of SFRSCC mixtures vary.

Besides, obtaining SFRSCC mixtures under the influence of many variables means performing a large number of trial
As a result of these, it can be said that this study aims to predict the fresh concrete class by using machine-learning methods by taking into consideration all mixture inputs of SFRSCC. For this purpose, many papers investigated in the literature and SFRSCC mixture ratios and fresh concrete test results were picked up from the documents having the sample data. These data are presented in Table 1 for both slump-flow and v-funnel.

Different parameters of eleven, which affect the fresh concrete properties of SFRSCC, are taken into account as the inputs in the analysis. The minimum and maximum subscript shown in Table 1 indicate the minimum and maximum amount of data in the reference work, respectively. A wide range of input values increases the reliability of the outputs and the scope of the study. Figure 1 and Figure 2 show the histogram of the data used in the designed models. These histograms show the distribution, mean values and standard deviation values of the analyzed data. When the entire database is taken into consideration, the amount of cement (C), silica fume+stone powder (S), fly ash (FA), maximum aggregate size (Dmax), fine aggregate (Fi), coarse aggregate (CA), chemical additive (A), steel fiber (StF), diameter of fiber (FD), length of fiber (FL), diameter of flow (SF), and time of v-funnel (VF) range from 250 to 824 kg/m$^3$, 0 to 623 kg/m$^3$, 0 to 250 kg/m$^3$, 8 to 19 mm, 315 to 1087 kg/m$^3$, 420 to 1308 kg/m$^3$, 120 to 235 L, 2.9 to 20 kg/m$^3$, 10 to 117.8 kg/m$^3$, 0.16 to 1.0 mm, 6 to 60 mm, 55 to 74 cm and 2.7 to 22 s, respectively. In the present study, mineral additives are classified into two groups. Silica fume, silica flour and stone dust, which reduce the workability of the fresh concrete, were taken as a group, and fly ash, on the other hand, which increases the workability, was chosen as a second group. When assessing the fresh concrete properties of SFRSCC, the workability classes are determined using the test results. The workability class clearly defines the fresh concrete properties of the concretes. In this study, the classes of the slump-flow and v-funnel experiments are predicted. These classifications are based on EFNARC (2005) [32]. The classification limits of fresh concrete tests and the total number of data used for each classification are presented in Table 2.

### IV. MATERIAL AND METHODS

Two different machine-learning methods were used to predict the performance of SFRSCC. These methods are Q-SVM and W-KNN Models.
FIGURE 1. Range of design parameters for slump-flow as histograms.
FIGURE 2. Range of design parameters for v-funnel as histograms.
TABLE 2. Classification used for fresh properties of SFRSCC.

| Type of test | Slump-flow (cm) | V-funnel (s) |
|--------------|-----------------|--------------|
| Classes      | SF1             | SF2          |
| Range of values | 55 to 65      | 66 to 75    |
| Number of data | 22             | 28           |

W-KNN. The classification methods and evaluation metrics used are defined in detail below.

A. QUADRATIC SUPPORT VECTOR MACHINES

SVM was introduced by Vapnik to solve the classification problems [48]. The basis of the SVM method is a statistical learning theory and a structural risk minimization. The SVM aims to learn the boundary between the two classes by mapping input values to a high-dimensional area. For Linear SVM to be a maximum margin class, the data set must be separated linearly. In this case, the vector \( \mathbf{w} \) is defined in detail below.

Let’s have a training set \( (x_i, y_i) \), \( 1 \leq i \leq N \). \( x_i \) input values and \( y_i \) show the size of the input values [50]. The \( y_i \) gives the output values. In SVM, the aim is to ensure that all points bearing the same set are on the same side of the hyperplane and to form hyperplanes [51].

\[
y_i (w \cdot x_i + b) > 0, \quad i = 1, \ldots, N \tag{1}
\]

If there is hyperplane (1), it means that the data set can be separated linearly. In this case, \( w \) and \( b \) are continuously resized, and the Eq. (2) is obtained.

\[
\min_{1 \leq i \leq N} y_i (w \cdot x_i + b) \geq 1, \quad i = 1, \ldots, N \tag{2}
\]

In other words, the distance between the closest point and the hyperplane is \( 1/|w| \). Thus, the Eq. (1) is converted to the Eq. (3).

\[
y_i (w \cdot x_i + b) > 1 \tag{3}
\]

The first objective of the SVM is to find the optimal separator hyperplane (OSH) among the distal hyperplanes which are the distance to the proximate point is maximal [50]. As the distance to the nearest point is \( 1/|w| \), OSH decides to minimize \( |w|^2 \) under constraints Eq. (2) [52]. The amount of \( 2/|w| \) is called a margin, and so OSH is the separator hyperactive that maximizes the margin. The generalization ability is the margin, which has been defined by Vapnik [53] and Bartlett and Shawe-Taylor [54] a better generalization is defined by Chapelle et al. [50]. Since \( |w|^2 \) is convex, it can be achieved with Lagrange multipliers to be minimized under linear constraints Eq. (2). If we use \( W(\alpha) = (\alpha_1, \ldots, \alpha_N) \), \( N \) without any negative Lagrange multipliers Eq. (2), our optimization problem maximizes \( \alpha_i \) and with constraint \( \sum_{i=1}^{N} y_i \alpha_i = 0 \). Standard quadratic programming should be used to ensure this [55].

\[
w(\alpha) = \sum_{i=1}^{N} \alpha_i - \frac{1}{2} \sum_{i,j=1}^{N} \alpha_i \alpha_j y_i y_j x_i \cdot x_j \tag{4}
\]

When the vector \( \alpha^0 = (\alpha^0_1, \ldots, \alpha^0_N) \) solution of the maximization problem is found in Eq. (4), the OSH \( (w_0 b_0) \) has the Eq. (5).

\[
w_0 = \sum_{i=1}^{N} \alpha^0_i y_i x_i \tag{5}
\]

The support vectors are the point that provides the Eq. (3). Support vectors are the points where \( \alpha^0_i > 0 \) Eq. (3). Considering the expansion Eq. (5) of \( w_0 \), the hyperplane decision function is shown that Eq. (6).

\[
f(x) = \text{sgn} \left( \sum_{i=1}^{N} \alpha^0_i y_i x_i \cdot x + b_0 \right) \tag{6}
\]

B. K-NEAREST NEIGHBOR

NN algorithm is the oldest and the simplest method of classification. With the increase of computing power of computers, it has gained great importance and has become one of the most widely used methods for classification [19]. Because NN is a distance-based method, it is more suitable for application in numerical datasets than categorical datasets. When the basic logic of NN is applied to the algorithm training set, the closest point to the query is found in the training set, and the query is assigned to the class label of that point. KNN is an extension of NN, and the query is included in a class according to the majority of the tags of the nearest k-neighbor. The best known distance calculation is that of Euclidian equation [24]. The equation for Euclidean calculation is described as follow:

\[
\text{Euclidean}_{ij} = \sqrt{\sum_{k=1}^{n} (x_{ik} - x_{jk})^2} \tag{7}
\]

1) WEIGHTED K-NEAREST NEIGHBOR

W-KNN algorithm was first introduced by [56]. In the W-KNN, close neighbors are weighed more heavily than their distant neighbors using the distance-weight function. The \( w_i \) weight of the NN in question \( x’ \) in the iteration \( i \) is shown in the following Eq. (8) [57], as shown at the bottom of this page.

Then the class label is determined by voting according to the k value to determine the class to which the query will be assigned. The smallest distance neighbor is weighed more heavily than the larger distance. The nearest neighbor’s weight is 1, and the farthest neighbor’s weight is 0, then the
weights of the other neighbors are scaled linearly according to the distance between them.

C. EVALUATION METRICS

In this article, Evaluation metrics that are commonly used to measure classifier performance have been selected. These metrics are accuracy, sensitivity, specificity, precision and F-measure. The higher each of these metrics, the better the predictor’s predictive power. The metrics used in the article are described below. The TP value is true positive, TN is true negative, FP is false positive, and FN is a false negative.

Accuracy: It is the ratio of accurate estimates made by the classifier to all estimates. The equation is given in Eq. (9).

\[
\text{accuracy} = \frac{TP + TN}{TP + FN + FP + TN} \tag{9}
\]

Sensitivity (TPR): The value of those who are considered to be positive is the ratio of the true value to the positive ones. Sensitivity formula is described as follow:

\[
\text{sensitivity} = \frac{TP}{TP + FN} \tag{10}
\]

Specificity (TNR): It gives the ratio of those estimated negative by the classifier to the negative ones. Specificity formula is described as follow:

\[
\text{specificity} = \frac{TN}{TN + FP} \tag{11}
\]

Precision: Among positive variables, it gives the proportion of which predicted positively by the classifier. Precision formula is described as follow:

\[
\text{precision} = \frac{TP}{TP + FP} \tag{12}
\]

F-measure; Sensitivity and precision are the mean values of the blend. The high F-measure value indicates that the system has a high predictive ability. It is described as follow:

\[
F - \text{measure} = 2 \times \frac{\text{precision} \times \text{sensitivity}}{\text{precision} + \text{sensitivity}} \tag{13}
\]

V. THEORY

It has been tried to predict to fresh concrete classes of SFRSCCs with different mixing ratios. W-KNN and Q-SVM were used to classify the results of slump-flow and V-funnel experiments. Four different models are designed to classify the performance of SFRSCC. Two different data sets were used for slump-flow and v-funnel experiments.

In both models designed using W-KNN and Q-SVM; cement, silica flour, silica fume, stone flour, fly ash, Dmax, sand, coarse aggregate, water, chemical additive, amount of steel fiber, fiber diameter and fiber length are taken as input parameters. In the preprocessing, the sum of the silica flour, silica fume, and stone flour values was taken as a single input parameter. The output parameters were determined as two.
classes according to EFNARC (2005) in both models [32]. The designed models are shown in Figure 3. For the performance measurement of SFRSCC, 67 sample data were used in the slump-flow experiment, and 49 sample data were used in the V-funnel experiment.

To predict the class labels of the slump-flow experiment, the Euclidean distance was used for the distance in W-KNN, and the k value was taken as 10. In the model designed using Q-SVM, the quadratic kernel is used as the kernel function. In order to predict the class labels of the V-funnel experiment, the Euclidean distance was used for the distance in W-KNN, and the k value was taken as 10. In the model designed using Q-SVM, the quadratic kernel is used as the kernel function.

VI. RESULT AND DISCUSSION

In the literature, the determination of fresh and hardened concrete properties is generally used for concrete performance. The models designed to predict the fresh and hardened concrete properties of 90% and above indicate that the results are satisfactory. For SFRSCCs, however, the acceptable lower limit value for fresh concrete properties is around 60% [1], [58].

In this study, 5-k cross-validation was used to measure the performances of the four different models. Two different data sets are randomly divided into five equal parts. While sequentially each piece was used as a testing data set, the remaining four parts were used as a training data set.

With this method, all the available data are used as testing data, and it is aimed to achieve more reliable and stable results. Table 3 shows the confusion matrixes for all results after each data is used as the test data. In Table 3, the slump-flow and v-funnel class labels show which method predicts the correct and incorrect data in which classes.

As seen in Table 3, in the slump-flow experiment, W-KNN correctly predicted 21 of 28 data in SF1 class and 30 of 39 data in SF2 class correctly. In the SF2 class of the W-KNN, the correct rate of knowledge is 76.92%, and the correct rate in the SF2 class is 75%. Q-SVM correctly predicted 22 of 28 data and 34 of 39 data. The correct knowledge rate was 78.57% and 87.18%, respectively. In the V-funnel experiment, W-KNN and Q-SVM predicted 20 of the 22 data in the VF1 class and achieved the success of 90.91% in both methods. W-KNN has correctly predicted 24 of the 27 data in the VF2 class and achieved 88.89% success. The Q-SVM predicted 25 of 27 data and achieved a value of 92.59%.

The accuracy, sensitivity, specificity, precision and f-measure values were calculated for the comparison of the four different designed models. The results of the study are shown in Table 4. As seen from Table 4, in the models designed for the slump-flow experiment the Q-SVM

| TABLE 3. Confusion matrices of designed models; (a) W-KNN for slump-flow; (b) Q-SVM for slump-flow; (c) W-KNN for v-funnel; (d) Q-SVM for v-funnel. |
|-----------------------------------------------|
| ![Confusion Matrix for Slump-Flow](image1)     |
| ![Confusion Matrix for V-funnel](image2)      |

| TABLE 4. The evaluation metrics of the designed models using W-KNN and Q-SVM. |
|-----------------------------------------------|
| ![Evaluation Metrics](image3)                |

| Slump-flow | Accuracy | Sensitivity | Specificity | Precision | F-measure |
|------------|----------|-------------|-------------|-----------|-----------|
| W-KNN      | 0.7612   | 0.7500      | 0.7692      | 0.7000    | 0.7241    |
| Q-SVM      | 0.8358   | 0.7857      | 0.8718      | 0.8148    | 0.8000    |

| V-funnel   | Accuracy | Sensitivity | Specificity | Precision | F-measure |
|------------|----------|-------------|-------------|-----------|-----------|
| W-KNN      | 0.8980   | 0.9091      | 0.8889      | 0.8696    | 0.8889    |
| Q-SVM      | 0.9184   | 0.9091      | 0.9259      | 0.9091    | 0.9091    |
algorithm was successful in all values according to W-KNN. Q-SVM performed better at 9.8% inaccuracy, 4.7% in sensitivity, 13.3% in specificity, 17% in precision and 10.4% in f-measure compared to KNN. The graphical representation of the calculated values and the differences between the two models are shown in Figure 4 (a). The slump-flow experiment was modeled on Q-SVM with 0.83 accuracies, better than W-KNN as seen from Figure 4 (a). In the models designed for the V-funnel experiment, the W-KNN and Q-SVM methods achieved closer results. In the models designed for the V-funnel test, the sensitivity values of the W-KNN and Q-SVM methods were the same, whereas, according to the specificity value, the Q-SVM algorithm at F-measure was found to be more successful than the W-KNN. In the comparison between the two methods, the Q-SVM performed better than 2.2% for accuracy, 4.1% for specificity, 4.5% for precision and 2.2% for F-measure. The graphical representation of the calculated values and the differences between the two models are shown in Figure 4 (b). In the V-funnel experiment as in the slump-flow experiment, Q-SVM was modeled by finding better results than W-KNN as seen from Figure 4 (b).

The f-measure value, which is the harmonic means of the sensitivity and specificity values, is a more accurate measure of the overall success of the system. When the models were evaluated with the f-measure value, Q-SVM was observed that it was more successful in the slump-flow experiment by 10.4% and the V-funnel experiment by 2.2%.

When the evaluation metrics of the designed models are examined, it is clear that the prediction of the fresh concrete properties of SFRSCC is a very significant development. Because the trial mixes made before the production of SFRSCC cause time and cost effective. It is clear that the designed models will provide a considerable benefit in terms of time and cost. Designed models have reduced the number of trial mixes by nearly 80% to achieve standard SFRSCC mixtures. In addition to the cost and labor gains, it will be easier to expand this particular type of concrete.

Classical statistical methods require meaningful data, and so provide high accuracy just in narrow value ranges. Therefore, the methods obtained as a result of these methods are limited in a narrow solution area. However, machine-learning systems can achieve high accuracy results by using data that seem to be meaningless and have a wide range of values. Figure 1 and Figure 2 shows the range values for the input values used in slump-flow and v-funnel tests, respectively. Obviously, such a small and disorganized group of data cannot be obtained by using classical statistical methods. However, high accuracy results were obtained using W-KNN and Q-SVM.

VII. CONCLUSION
A SFRSCC is a particular type of concrete formed using steel fiber. Although SFRSCC is a particular type of concrete with superior fresh and hardened properties, it is hard to obtain
SFRSCC mixtures with suitable mixing ratios. The main reason for this obstacle is the need to make a large number of trial mixtures to obtain SFRSCC mixtures with suitable fresh concrete properties. The main reason for the high amount of test mixtures is fresh concrete properties. As many parameters affect the fresh properties of SFRSCC, mixtures with suitable fresh concrete properties can only be determined by a large number of test mixtures. To contribute to the elimination of the impediment to the production and expansion of SFRSCC, the models have been designed for the most widely used slump-flow and v-funnel experiments in SFRSCC under the influence of different parameters. The results of the study are listed below.

- The fresh concrete properties of SFRSCC have been predicted with high accuracy using classification methods.
- Four models were developed by using W-KNN and Q-SVM methods to estimate fresh concrete properties. When W-KNN is used, the success rates of the model are 0.76 and 0.90 for the slump-flow and v-funnel values, respectively; When Q-SVM was used, the success rates were 0.84 and 0.92 for slump-flow and v-funnel values, respectively. It is seen that the models developed based on the 11 parameters predicted successfully.
- Although the designed models predict the SFRSCC’s fresh concrete properties with high accuracy, Q-SVM seems to be more successful than the W-KNN. For this reason, it is recommended to use Q-SVM method in concrete studies.
- The number of trial mixes is expected to decrease by at least the lowest accuracy (76%) with the designed models. Thus, it is clear that the time, cost and labor loss caused by the trial mixes will decrease. In addition, it is predicted that the models developed in the production and expansion of the SFRSCC will contribute.

As a result of the study, the results obtained by using machine learning methods have been shown to be an acceptable value. It was revealed that the performance of fresh concrete of SFRSCC can be predicted by machine learning methods. In this study, a model that can be used in slump-flow and v-funnel experiments used in determining the fresh concrete performance of SFRSCC with 83% and 91% success rates of the Q-SVM method has been designed.

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