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Research Article

Prediction of Splitting Tensile Strength from Cylinder Compressive Strength of Concrete by Support Vector Machine

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Compressive strength and splitting tensile strength are both important parameters that are utilized for characterization concrete mechanical properties. This paper aims to show a possible applicability of support vector machine (SVM) to predict the splitting tensile strength of concrete from compressive strength of concrete, a SVM model was built, trained, and tested using the available experimental data gathered from the literature. All of the results predicted by the SVM model are compared with results obtained from experimental data, and we found that the predicted splitting tensile strength of concrete is in good agreement with the experimental data. The splitting tensile strength results predicted by SVM are also compared to those obtained by using empirical results of the building codes and various models. These comparisons show that SVM has strong potential as a feasible tool for predicting splitting tensile strength from compressive strength.

1. Introduction

Compressive strength (f_c) and splitting tensile strength (f_{spt}) are two significant indexes in the design of concrete structure. Tensile strength is important for plain concrete structures such as dam under earthquake excitations. Other structures for example pavement slabs and airfield runways, which are designed based on bending strength, are subjected to tensile stresses. Therefore, in the design of these structures, tensile strength is more important than compressive strength [1, 2]. Ideally, the splitting tensile strength is measured directly on concrete samples under uniform stresses. However, this is not always easy from an experimental point of view. To avoid the demanding and time-consuming direct measurements of the splitting tensile strength, engineers and researchers have tried to predict the splitting tensile using theoretical and empirical approaches based on compressive strength. Generally, tensile strength of concrete was often assumed proportional to the square root of its compressive strength [3]. However, there have been very few published works dealing with experimental and analytical researches of the relation of f_{spt} and f_c of concretes [4].

Generally, the splitting tensile strength can be established from compressive strength. National building codes propose various formulas for the splitting tensile strength f_{spt} and compressive strength f_c. Various relationships for concrete were given as follows:

$$\text{CEB-FIP (1991)} \quad f_{\text{spt}} = 0.3(f_c)^{2/3}, \tag{1}$$

$$\text{ACI363R-92 (1992)} \quad f_{\text{spt}} = 0.59(f_c)^{1/2}, \tag{2}$$

$$\text{ACI318-99 (1999)} \quad f_{\text{spt}} = 0.56(f_c)^{1/2}, \tag{3}$$

where f_{spt} and f_c are expressed in MPa.

Larrad and Malier [5] found that the calculated f_{spt} obtained from the French regulations were in good agreement with experimental data. Kim et al. [6, 7] found that the ACI model overestimates the value for concrete with compressive strength less than 20 MPa and underestimates the value for concrete with compressive strength over 30 MPa. Zain et al. [2] determined relationships between tensile strength with compressive strength, concrete age and water/binder (W/B). Shaaban and Gesund [8] investigated the splitting tensile strength and compressive strength of steel fiber reinforced concrete but, unfortunately, did not analyze the relationship between the tensile strength and compressive strength. Choi and Yuan [4] investigated the relationship between the tensile strength and compression strength of glass fiber reinforced concrete and polypropylene fiber reinforced concrete. Xu and Shi [1] developed the formulation between the f_{spt} and f_c of steel fiber reinforced concrete. Mathematical regression models are usually imperfect description of complex physical phenomena. The accuracy of the estimated result depends on the size of available data. Saridemir [9] proposed for f_{spt} prediction from cylinder f_c of concrete or age of specimen (AS) and cylinder f_c of concrete by gene expression programming (GEP). The support vector machine (SVM) is a new, efficient, and novel approach to improve generalization performance, and it can attain a global minimum. SVM achieves good generalization ability by adopting a structural risk minimization induction principle that aims at minimizing a bound on generalization error of a model rather than minimizing the error on the training data only. It has the ability to avoid overtraining and has better generalization capability than artificial neural networks (ANN) model. Moreover, the SVM can always be updated to get better results by presenting new training examples as new data become available.

In this paper, support vector machine is applied to predict the splitting tensile strength of concrete using the datum collected by Saridemir [9]. Compressive strength used to predict the splitting tensile strength is considered as input in SVM model that is compared with experimental data and other methods. The mean absolute parentage error (MAPE), root-mean-squared error (RMSE), and R-square (R^2) are used as the criteria to compare the performance of SVM models and other models.

2. Support Vector Machine

SVM is a machine-learning algorithm based on statistical learning theory. The main idea of the SVM is to transform the input space into a high-dimensional space by a nonlinear transformation defined by an inner product function. SVM calculation takes the form of a problem in convex quadratic optimization, ensuring that the solution is optimal. It is better than the traditional artificial neural networks, which is based on the traditional minimization principle of experience risk [10]. The SVM has a good ability to generalize and resolve some practical problems such as small samples, nonlinearity, and high-dimensional input space.

In this section, a brief description of the process of constructing a SVM for a regression problem is presented. There are three distinct characteristics to consider when an SVM is used to solve a regression problem [11]. First, the SVM estimates the regression by a set of linear functions that are defined in a high-dimensional space. Second, the SVM carries out the regression estimation by risk minimization, where the risk is measured using Vapnik's ε-insensitive loss function. Third, the SVM uses a risk function consisting of the empirical error and a regularization term, which is derived from the structural risk minimization (SRM) principle.

Table 1: Parameters of SVM-I and SVM-II.

	SVM-I		SVM-II	
Kernel	Radial basis function	Polynomial	Radial basis function	Polynomial
C	500000	160000	820000	870000
ε	0.10	0.10	0.04	0.05
Parameter	$\gamma = 0.01$	$d = 2$	$\gamma = 0.10$	$d = 3$

Consider a set of training samples $\{x_i, y_i\}$, $i = 1, 2, \ldots n$, $x_i \in R^d$, $y_i \in R$, where x_i is an input vector, y_i is the corresponding output value, and n is the number of training samples. The regression problem is to select a function that predicts the actual value of y as closely as possible, with a precision of ε. Therefore, the purpose of the SVM is to seek the optimum regression function:

$$f(x) = \omega \cdot x + b, \tag{4}$$

where, $\omega \in R^n$ and $b \in R$, ω is an adjustable weight vector, b is the scalar threshold; R^n is n-dimensional vector space, and x is one-dimensional vector space.

Following statistical theory, SVM determines the regression function by minimizing an objective function. The parameters ω and b of the regression function are estimated by minimizing the regularized risk function as follows:

Minimize

$$\frac{1}{2}\|\omega\|^2 + C\sum_{i=1}^{n}(\xi_i + \xi_i^*). \tag{5}$$

Subject to

$$y_i - [(\omega \cdot x_i) + b] \le \varepsilon + \xi_i, \tag{6}$$

$$[(\omega \cdot x_i) + b] - y_i \le \varepsilon + \xi_i^*, \tag{7}$$

$$\xi_i \ge 0, \quad \xi_i^* \ge 0, \quad i = 1, 2, \ldots n, \tag{8}$$

where $C > 0$ is a penalty factor, ξ and ξ^* are slack variables. ε is the insensitive loss function and can be described in the following way:

$$L_\varepsilon(y) = \begin{cases} |f(x) - y| - \varepsilon & |y - f(x)| \ge \varepsilon \\ 0 & \text{otherwise.} \end{cases} \tag{9}$$

By introducing Lagrangian multipliers and maximizing (3), the dual optimization problem can be expressed as

Maximize

$$\sum_{i=1}^{n} y_i(\alpha_i^* - \alpha_i) - \varepsilon\sum_{i=1}^{n}(\alpha_i^* + \alpha_i) - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)(x_i, x_j). \tag{10}$$

Table 2: Comparison of experimental results to training results of RBF Polynomial of SVM-I, and other models.

f_c (MPa)	f_{spt} (MPa)	GEP-I [9]	ACI 363R	ACI 318	CEB-FIP	Regression [9]	RBF	Polynomial
26.33	3.07	−0.72	−0.04	−0.20	−0.41	−0.52	−0.30	−0.29
35.82	3.12	−0.18	0.41	0.23	0.14	−0.02	0.34	0.01
30.93	3.21	−0.57	0.07	−0.10	−0.25	−0.39	−0.33	−0.30
37.42	2.07	0.97	1.54	1.36	1.29	1.12	0.00	1.14
29.10	3.01	−0.49	0.17	0.01	−0.17	−0.29	0.01	−0.17
28.03	3.41	−0.95	−0.29	−0.45	−0.64	−0.76	−0.79	−0.53
36.98	3.25	−0.24	0.34	0.16	0.08	−0.09	0.37	−0.12
31.65	3.39	−0.71	−0.07	−0.24	−0.39	−0.53	−1.07	−0.40
38.58	3.16	−0.05	0.50	0.32	0.27	0.09	0.37	0.16
81.00	6.60	−1.10	−1.29	−1.56	−0.98	−1.40	−0.06	−1.19
68.00	5.90	−1.11	−1.03	−1.28	−0.90	−1.24	−1.76	−0.99
60.00	5.00	−0.65	−0.43	−0.66	−0.40	−0.70	−0.22	−0.60
54.00	4.70	−0.69	−0.36	−0.58	−0.41	−0.68	−0.15	−0.68
39.08	3.11	0.04	0.58	0.39	0.34	0.17	0.76	0.13
22.33	2.29	−0.20	0.50	0.36	0.09	0.01	0.25	0.39
23.23	2.19	−0.04	0.65	0.51	0.25	0.16	0.32	0.49
22.89	2.38	−0.25	0.44	0.30	0.04	−0.05	0.36	0.34
22.16	2.17	−0.09	0.61	0.47	0.20	0.11	0.34	0.50
20.48	2.15	−0.18	0.52	0.38	0.10	0.02	0.07	0.48
20.82	1.99	0.00	0.70	0.57	0.28	0.21	0.02	0.65
22.83	2.41	−0.28	0.41	0.27	0.00	−0.08	0.10	0.25
25.14	2.62	−0.34	0.34	0.19	−0.05	−0.14	0.12	0.12
25.60	2.69	−0.38	0.30	0.14	−0.08	−0.19	−0.15	0.09
35.20	3.20	−0.29	0.30	0.12	0.02	−0.13	0.39	−0.10
44.40	2.90	0.57	1.03	0.83	0.86	0.65	0.76	0.62
37.60	2.40	0.66	1.22	1.03	0.97	0.80	0.00	0.84
41.80	3.60	−0.29	0.21	0.02	0.01	−0.18	0.12	−0.20
42.00	3.50	−0.17	0.32	0.13	0.12	−0.07	0.47	−0.10
38.30	2.70	0.40	0.95	0.77	0.71	0.53	0.41	0.51
55.40	3.40	0.71	0.99	0.77	0.96	0.69	0.00	0.78
54.00	2.80	1.23	1.54	1.32	1.49	1.22	0.00	1.22
48.60	2.80	0.91	1.31	1.10	1.20	0.96	0.00	0.94
56.50	4.10	0.07	0.33	0.11	0.32	0.04	−0.06	0.09
47.00	3.90	−0.28	0.14	−0.06	0.01	−0.22	0.19	−0.22
45.69	4.19	−0.65	−0.20	−0.40	−0.36	−0.57	−0.37	−0.59
41.71	3.09	0.22	0.72	0.53	0.52	0.32	0.32	0.33
42.49	3.74	−0.38	0.11	−0.09	−0.09	−0.29	−0.53	−0.27
33.69	2.93	−0.11	0.49	0.32	0.20	0.05	0.40	0.16
37.30	3.14	−0.10	0.46	0.28	0.21	0.04	0.49	0.07
24.75	2.62	−0.37	0.32	0.17	−0.07	−0.17	−0.21	0.11
26.96	2.68	−0.28	0.38	0.23	0.02	−0.09	0.36	0.07
22.14	2.35	−0.27	0.43	0.28	0.02	−0.07	0.16	0.32
23.91	2.24	−0.04	0.64	0.50	0.25	0.16	0.03	0.44
41.00	3.90	−0.63	−0.12	−0.31	−0.33	−0.52	−0.94	−0.49
42.00	4.00	−0.67	−0.18	−0.37	−0.38	−0.57	−0.03	−0.60
57.68	4.26	−0.04	0.22	−0.01	0.22	−0.07	0.57	−0.02
45.75	4.10	−0.57	−0.11	−0.31	−0.26	−0.48	−0.28	−0.45
38.10	3.62	−0.54	0.02	−0.16	−0.22	−0.40	−0.19	−0.37
31.95	3.31	−0.61	0.02	−0.14	−0.29	−0.43	−0.27	−0.40

Table 2: Continued.

f_c (MPa)	f_{spt} (MPa)	GEP-I [9]	ACI 363R	ACI 318	CEB-FIP	Regression [9]	RBF	Polynomial
18.20	1.90	−0.10	0.62	0.49	0.18	0.12	−0.24	0.68
28.70	2.70	−0.20	0.46	0.30	0.11	−0.01	−0.20	0.23
23.90	2.30	−0.11	0.58	0.44	0.19	0.10	−0.03	0.38
43.70	3.30	0.11	0.60	0.40	0.42	0.22	0.44	0.21
24.60	2.30	−0.07	0.63	0.48	0.24	0.14	−0.01	0.45
43.00	3.50	−0.13	0.37	0.17	0.18	−0.02	0.00	0.00
14.20	1.80	−0.28	0.42	0.31	−0.04	−0.08	−0.29	0.63
36.70	3.20	−0.21	0.37	0.19	0.11	−0.05	−0.48	0.01
22.70	1.70	0.41	1.11	0.97	0.71	0.62	0.35	0.95
35.30	2.40	0.51	1.11	0.93	0.83	0.67	0.00	0.74
13.60	1.30	0.18	0.88	0.77	0.41	0.38	0.79	1.12
28.60	1.70	0.79	1.46	1.29	1.11	0.99	1.40	1.14
26.60	2.40	−0.04	0.64	0.49	0.27	0.17	−0.01	0.42
43.50	2.90	0.50	0.99	0.79	0.81	0.61	0.52	0.57
30.90	2.40	0.24	0.88	0.71	0.55	0.42	0.48	0.51
49.90	3.80	−0.03	0.37	0.16	0.27	0.03	0.39	0.04
32.20	3.00	−0.28	0.35	0.18	0.04	−0.10	−0.09	0.01
57.80	3.50	0.72	0.99	0.76	0.98	0.70	0.33	0.81
26.80	2.40	−0.02	0.65	0.50	0.29	0.18	0.47	0.44
36.50	2.90	0.08	0.66	0.48	0.40	0.24	0.27	0.26
65.60	4.40	0.26	0.38	0.14	0.48	0.15	0.14	0.36
30.30	2.40	0.20	0.85	0.68	0.52	0.39	1.37	0.54
52.80	3.80	0.14	0.49	0.27	0.42	0.17	−0.39	0.23
40.60	3.50	−0.27	0.26	0.07	0.04	−0.14	0.15	−0.13
52.30	4.20	−0.29	0.07	−0.15	0.00	−0.26	0.10	−0.24
41.20	3.20	0.06	0.59	0.39	0.38	0.19	0.65	0.22
72.80	5.10	−0.05	−0.07	−0.32	0.13	−0.24	0.03	−0.05
41.20	3.20	0.06	0.59	0.39	0.38	0.19	0.65	0.22
72.80	5.10	−0.05	−0.07	−0.32	0.13	−0.24	0.03	−0.05
72.80	5.10	−0.05	−0.07	−0.32	0.13	−0.24	0.03	−0.05
41.80	3.30	0.00	0.51	0.32	0.31	0.12	0.42	0.10
68.40	4.10	0.71	0.78	0.53	0.92	0.57	0.38	0.76
42.30	2.90	0.43	0.94	0.74	0.74	0.54	0.00	0.57
59.10	3.80	0.50	0.74	0.51	0.75	0.46	0.25	0.60
41.30	3.70	−0.43	0.09	−0.10	−0.12	−0.31	−0.19	−0.27
59.70	4.10	0.23	0.46	0.23	0.48	0.19	0.14	0.30
42.30	3.20	0.13	0.64	0.44	0.44	0.24	0.71	0.27
75.10	5.10	0.08	0.01	−0.25	0.24	−0.14	0.67	−0.05
48.50	3.70	−0.01	0.41	0.20	0.29	0.06	0.08	0.09
81.90	4.80	0.75	0.54	0.27	0.86	0.44	0.94	0.53
41.30	3.30	−0.03	0.49	0.30	0.28	0.09	0.21	0.13
67.10	4.40	0.34	0.43	0.19	0.55	0.22	0.68	0.36
42.00	3.20	0.11	0.62	0.43	0.42	0.23	0.77	0.20
70.10	4.30	0.61	0.64	0.39	0.80	0.45	0.65	0.58
44.80	3.40	0.08	0.55	0.35	0.38	0.17	0.36	0.21
65.40	4.00	0.65	0.77	0.53	0.87	0.54	0.67	0.70
38.70	3.50	−0.39	0.17	−0.02	−0.07	−0.24	0.40	−0.21
56.40	4.30	−0.16	0.13	−0.09	0.11	−0.16	−0.25	−0.14
42.40	3.20	0.13	0.64	0.45	0.45	0.25	0.41	0.25

Table 2: Continued.

f_c (MPa)	f_{spt} (MPa)	GEP-I [9]	ACI 363R	ACI 318	CEB-FIP	Regression [9]	RBF	Polynomial
67.70	4.80	−0.03	0.05	−0.19	0.18	−0.16	0.27	−0.03
50.70	3.60	0.22	0.60	0.39	0.51	0.26	0.48	0.26
81.10	4.80	0.70	0.51	0.24	0.82	0.41	0.62	0.52
42.00	3.20	0.11	0.62	0.43	0.42	0.23	0.77	0.20
48.90	3.60	0.11	0.53	0.32	0.41	0.18	0.61	0.21
85.30	5.80	−0.07	−0.35	−0.63	0.01	−0.42	0.32	−0.37
52.30	4.20	−0.29	0.07	−0.15	0.00	−0.26	0.10	−0.24
85.10	5.80	−0.08	−0.36	−0.63	0.00	−0.43	−0.34	−0.42
49.70	4.20	−0.44	−0.04	−0.25	−0.14	−0.38	−0.49	−0.36
71.20	5.30	−0.33	−0.32	−0.57	−0.15	−0.50	−0.52	−0.33
51.90	3.80	0.09	0.45	0.23	0.37	0.12	0.36	0.17
87.70	6.10	−0.24	−0.57	−0.86	−0.18	−0.63	−0.05	−0.66
51.90	3.80	0.09	0.45	0.23	0.37	0.12	0.36	0.17
87.70	6.10	−0.24	−0.57	−0.86	−0.18	−0.63	−0.05	−0.66
51.90	3.80	0.09	0.45	0.23	0.37	0.12	0.36	0.17
87.70	6.10	−0.24	−0.57	−0.86	−0.18	−0.63	−0.05	−0.66
53.80	4.10	−0.10	0.23	0.01	0.18	−0.09	−0.10	−0.06
85.30	5.10	0.63	0.35	0.07	0.71	0.28	1.02	0.33
58.70	4.40	−0.13	0.12	−0.11	0.13	−0.16	−0.26	−0.09
87.10	5.60	0.22	−0.09	−0.37	0.29	−0.15	−0.09	−0.20
49.30	4.50	−0.76	−0.36	−0.57	−0.47	−0.70	−1.35	−0.69
66.20	5.10	−0.41	−0.30	−0.54	−0.19	−0.52	−0.23	−0.40
53.10	3.80	0.16	0.50	0.28	0.44	0.18	0.50	0.33
84.30	5.60	0.07	−0.18	−0.46	0.17	−0.26	0.10	−0.15
86.70	6.03	0.03	−0.54	−0.80	−0.16	−0.60	0.02	−0.54
56.10	4.30	−0.17	0.12	−0.11	0.10	−0.18	−0.58	−0.17
52.10	3.80	0.10	0.46	0.24	0.38	0.13	0.11	0.16
78.50	5.00	0.36	0.23	−0.04	0.50	0.10	0.87	0.29
49.90	4.10	−0.33	0.07	−0.14	−0.03	−0.27	0.09	−0.26
87.50	5.10	0.75	0.42	0.14	0.81	0.37	0.48	0.29
55.10	4.40	−0.33	−0.02	−0.24	−0.06	−0.33	−0.11	−0.23
75.40	4.00	1.22	1.12	0.86	1.35	0.97	0.00	1.05
24.67	2.74	−0.50	0.19	0.04	−0.20	−0.29	−0.33	0.02
23.01	2.79	−0.66	0.04	−0.10	−0.36	−0.45	0.00	−0.09
32.03	3.03	−0.32	0.31	0.14	0.00	−0.14	−0.64	−0.03
28.78	2.93	−0.43	0.24	0.07	−0.11	−0.23	−0.43	0.00
33.60	2.03	0.77	1.39	1.22	1.09	0.95	1.30	1.06
23.30	3.04	−0.89	−0.19	−0.34	−0.59	−0.68	−1.25	−0.31

GEP-I model is developed by Saridemir [9] based on gene expression programming. Regression is regression-based formulation results by Saridemir [9].

Subject to

$$\sum_{i=1}^{n} \alpha_i = \sum_{i=1}^{n} \alpha_i^*, \quad 0 \le \alpha_i^* \le c, \; 0 \le \alpha_i \le c, \tag{11}$$

where the α_i, α_i^* are called Lagrangian multipliers. When the Lagrangian multipliers (α_i, α_i^*) are equal to zero, shows that the training object is irrelevant to the final solution; otherwise, the training samples with nonzero Lagrangian multipliers are called support vectors.

When linear regression is not appropriate, then the input data have to be mapped into a high-dimensional feature space through some nonlinear mapping. A nonlinear transformation $\phi(x)$ replaces the input x in (7), and the regression function can be written as

$$f(x) = \sum_{i=1}^{\text{nsv}} (\alpha_i - \alpha_i^*) k(x_i, x_j) + b, \tag{12}$$

where nsv is the number of support vectors and $k(x_i, x_j) = \phi(x_i) \cdot \phi(x_j)$, $k(x_i, x_j)$ is a kernel function. Any function satisfying Merce's condition can be used as the kernel function [12, 13]. Some popular kernel functions are

Table 3: Comparison of experimental results to testing results of RBF, polynomial of SVM-I, and other models.

f_c (MPa)	f_{spt} (MPa)	GEP-I [9]	ACI 363R	ACI 318	CEB-FIP	Regression [9]	RBF	Polynomial
44.80	3.80	−0.31	0.15	−0.05	−0.02	−0.23	−0.01	−0.33
56.20	4.40	−0.25	0.02	−0.20	0.00	−0.27	−0.41	−0.20
53.40	3.60	0.39	0.71	0.49	0.65	0.39	0.33	0.39
56.70	4.60	−0.42	−0.16	−0.38	−0.17	−0.45	−0.09	−0.36
64.50	4.80	−0.18	−0.06	−0.30	0.02	−0.30	−0.18	−0.12
66.50	4.70	0.03	0.11	−0.13	0.22	−0.11	0.10	0.01
65.40	4.30	0.37	0.47	0.23	0.57	0.24	0.21	0.43
73.80	4.90	0.23	0.17	−0.09	0.38	0.01	0.22	0.14
74.00	5.30	−0.16	−0.22	−0.48	−0.01	−0.39	−0.26	−0.15
72.50	5.00	0.06	0.02	−0.23	0.22	−0.15	0.24	−0.06
74.60	4.90	0.28	0.20	−0.06	0.42	0.04	0.06	0.15
77.90	5.50	−0.14	−0.29	−0.56	−0.03	−0.42	−0.36	−0.19
79.10	5.20	0.22	0.05	−0.22	0.33	−0.07	0.01	0.15
84.20	5.70	0.00	−0.29	−0.56	0.06	−0.37	−0.34	−0.28
83.30	5.90	−0.25	−0.52	−0.79	−0.18	−0.60	−0.60	−0.39
80.10	5.30	0.15	−0.02	−0.29	0.27	−0.13	−0.22	0.10
86.50	5.50	0.32	−0.01	−0.29	0.37	−0.07	−0.27	0.12
102.00	5.50	1.15	0.46	0.16	1.05	0.53	0.37	0.34
101.00	6.50	0.09	−0.57	−0.87	0.01	−0.51	−0.45	−0.60
111.00	6.20	0.92	0.02	−0.30	0.73	0.16	0.40	−0.17
94.50	5.80	0.45	−0.06	−0.36	0.42	−0.06	0.08	−0.01
118.00	6.20	1.28	0.21	−0.12	1.02	0.41	0.64	−0.14
19.00	2.30	−0.43	0.27	0.14	−0.16	−0.23	−0.04	−1.00
20.00	2.40	−0.46	0.24	0.10	−0.19	−0.26	−0.13	−0.96
28.60	2.90	−0.40	0.26	0.09	−0.09	−0.21	0.11	−0.67
28.90	3.00	−0.48	0.17	0.01	−0.17	−0.30	0.08	−0.82
36.10	3.30	−0.33	0.24	0.06	−0.02	−0.19	−0.11	−0.48
44.50	3.70	−0.23	0.24	0.04	0.07	−0.14	0.07	−0.26
23.00	2.50	−0.36	0.33	0.19	−0.07	−0.16	−0.37	−0.82
33.00	3.50	−0.72	−0.11	−0.28	−0.41	−0.56	−0.43	−1.02
58.00	4.20	0.05	0.29	0.06	0.30	0.01	−0.25	0.20
69.00	4.50	0.37	0.40	0.15	0.55	0.20	0.12	0.44
36.00	3.30	−0.34	0.24	0.06	−0.03	−0.19	−0.04	−0.45
42.80	3.90	−0.53	−0.04	−0.24	−0.23	−0.43	−0.19	−0.63
59.30	4.00	0.33	0.54	0.31	0.56	0.27	0.29	0.40
63.30	4.50	0.05	0.19	−0.04	0.26	−0.05	−0.18	0.20
67.70	4.70	0.10	0.15	−0.09	0.28	−0.06	0.26	0.07
77.00	5.10	0.21	0.08	−0.19	0.33	−0.06	−0.05	0.01
49.90	4.30	−0.51	−0.13	−0.34	−0.23	−0.47	−0.32	−0.45
96.70	5.70	0.63	0.10	−0.19	0.62	0.12	0.05	0.01
61.70	4.60	−0.14	0.03	−0.20	0.08	−0.22	−0.36	−0.08
73.20	5.10	0.00	−0.05	−0.31	0.15	−0.22	0.17	−0.03
86.50	5.50	0.32	−0.01	−0.29	0.37	−0.07	−0.27	0.12
92.30	5.90	0.23	−0.23	−0.52	0.23	−0.25	0.10	−0.19

(1) polynomial kernel function

$$K(x, y) = [(x + y) + 1]^d, \quad d = 1, 2, \ldots, n, \tag{13}$$

(2) radial basis function (RBF)

$$K(x, y) = \exp\left\{-\gamma \|x - y\|^2\right\} \gamma \geq 0, \tag{14}$$

(3) sigmoid kernel function

$$K(x, y) = \tan[\varphi(x \cdot y) + \theta], \tag{15}$$

where α_i, α_i^* satisfy $\alpha_i \alpha_i^* = 0$, $\alpha_i \geq 0$, and $\alpha_i^* \geq 0$.

Table 4: Comparison of experimental results to training results of RBF, polynomial of SVM-II, and other models.

f_c (MPa)	f_{spt} (MPa)	GEP-III [9]	ACI 363R	ACI 318	CEB-FIP	Regression [9]	RBF	Polynomial
77.90	5.45	−0.08	−0.24	−0.51	0.02	−0.33	0.48	0.32
57.10	3.13	1.03	1.33	1.10	1.32	1.15	1.74	1.45
71.60	4.90	0.11	0.09	−0.16	0.27	−0.02	0.81	0.51
44.10	3.91	−0.52	0.01	−0.19	−0.17	−0.23	0.28	−0.17
64.80	4.57	0.04	0.18	−0.06	0.27	0.03	0.73	0.42
42.60	3.66	−0.36	0.19	0.00	0.00	−0.05	0.47	−0.04
30.40	2.79	−0.26	0.46	0.30	0.13	0.17	0.46	0.00
46.80	3.89	−0.34	0.15	−0.06	0.01	−0.08	0.49	0.04
89.50	5.91	0.11	−0.33	−0.61	0.09	−0.36	0.73	0.41
66.90	4.55	0.19	0.28	0.03	0.39	0.14	0.96	0.59
76.10	5.47	−0.21	−0.32	−0.58	−0.08	−0.42	0.41	0.22
53.60	4.37	−0.41	−0.05	−0.27	−0.11	−0.25	0.47	−0.02
64.80	5.07	−0.46	−0.32	−0.56	−0.23	−0.47	0.23	−0.08
45.80	4.02	−0.53	−0.03	−0.23	−0.18	−0.26	0.40	−0.16
37.60	3.16	−0.17	0.46	0.27	0.21	0.19	0.63	0.14
53.10	4.08	−0.15	0.22	0.00	0.16	0.02	0.78	0.24
34.90	3.50	−0.68	−0.01	−0.19	−0.30	−0.29	0.12	−0.40
53.90	5.40	−1.42	−1.07	−1.29	−1.12	−1.27	−0.62	−1.00
46.50	3.80	−0.27	0.22	0.02	0.08	−0.01	0.60	0.07
13.80	1.70	−0.29	0.49	0.38	0.03	0.17	−0.42	−0.17
67.10	4.80	−0.05	0.03	−0.21	0.15	−0.10	0.64	0.35
20.30	3.40	−1.53	−0.74	−0.88	−1.17	−1.06	−1.26	−1.36
22.40	2.10	−0.09	0.69	0.55	0.28	0.38	0.38	0.10
61.40	4.30	0.12	0.32	0.09	0.37	0.16	0.79	0.51
33.10	3.00	−0.29	0.39	0.22	0.09	0.11	0.53	−0.03
79.00	5.60	−0.17	−0.36	−0.62	−0.08	−0.44	0.46	0.21
43.60	3.60	−0.24	0.30	0.10	0.12	0.06	0.59	0.10
25.60	2.42	−0.20	0.57	0.41	0.19	0.26	0.31	0.02
26.20	2.62	−0.36	0.40	0.25	0.03	0.10	0.23	−0.15
16.90	1.88	−0.25	0.55	0.42	0.10	0.23	−0.13	−0.10
14.90	1.71	−0.22	0.57	0.45	0.11	0.25	−0.38	−0.08
27.30	2.81	−0.48	0.27	0.12	−0.09	−0.03	0.19	−0.26
28.40	2.87	−0.47	0.27	0.11	−0.08	−0.02	0.22	−0.23
16.90	1.91	−0.28	0.52	0.39	0.07	0.20	−0.16	−0.13
16.90	2.11	−0.48	0.32	0.19	−0.13	0.00	−0.36	−0.33
30.90	2.92	−0.35	0.36	0.19	0.03	0.07	0.31	−0.10
32.30	3.08	−0.43	0.27	0.10	−0.04	−0.01	0.36	−0.17
19.60	2.22	−0.40	0.39	0.26	−0.04	0.08	−0.10	−0.22
19.10	2.08	−0.30	0.50	0.37	0.06	0.18	−0.11	−0.10
35.30	3.24	−0.40	0.27	0.09	−0.01	−0.01	0.38	−0.11
38.40	3.36	−0.32	0.30	0.11	0.05	0.04	0.57	−0.03
22.50	2.47	−0.45	0.33	0.19	−0.08	0.02	−0.05	−0.27
23.40	2.57	−0.49	0.28	0.14	−0.12	−0.02	−0.08	−0.29
31.00	2.90	−0.33	0.38	0.22	0.06	0.10	0.35	−0.06
17.00	2.30	−0.66	0.13	0.01	−0.32	−0.18	−0.60	−0.51
47.00	4.00	−0.44	0.04	−0.16	−0.09	−0.18	0.44	−0.09
37.00	3.60	−0.65	−0.01	−0.19	−0.27	−0.28	0.21	−0.35
42.00	4.00	−0.74	−0.18	−0.37	−0.38	−0.42	0.16	−0.39
54.00	4.60	−0.62	−0.26	−0.48	−0.31	−0.46	0.21	−0.24

Table 4: Continued.

f_c (MPa)	f_{spt} (MPa)	GEP-III [9]	ACI 363R	ACI 318	CEB-FIP	Regression [9]	RBF	Polynomial
42.00	4.40	−1.14	−0.58	−0.77	−0.78	−0.82	−0.24	−0.79
62.00	5.20	−0.75	−0.55	−0.79	−0.50	−0.72	0.03	−0.35
67.00	4.25	0.49	0.58	0.33	0.70	0.44	1.15	0.91
72.50	5.10	−0.04	−0.08	−0.33	0.12	−0.19	0.56	0.38
74.50	5.20	−0.03	−0.11	−0.37	0.11	−0.21	0.59	0.38
79.50	5.75	−0.29	−0.49	−0.76	−0.20	−0.57	0.30	0.11
78.00	5.15	0.22	0.06	−0.20	0.33	−0.03	0.83	0.60
85.00	5.75	0.02	−0.31	−0.59	0.05	−0.36	0.69	0.44
86.00	4.80	1.03	0.67	0.39	1.05	0.62	1.67	1.40
90.50	4.40	1.68	1.21	0.93	1.65	1.19	2.32	2.04
54.80	3.34	0.69	1.03	0.81	0.99	0.83	1.61	1.06
32.90	2.85	−0.16	0.53	0.36	0.23	0.25	0.68	0.11
34.50	2.92	−0.13	0.55	0.37	0.26	0.27	0.66	0.13
53.60	3.48	0.48	0.84	0.62	0.78	0.64	1.36	0.87
74.10	5.26	−0.11	−0.18	−0.44	0.03	−0.29	0.58	0.30
67.70	4.81	−0.03	0.04	−0.20	0.17	−0.09	0.68	0.37
84.20	6.57	−0.85	−1.16	−1.43	−0.81	−1.21	−0.25	−0.46
75.30	5.35	−0.13	−0.23	−0.49	0.00	−0.33	0.48	0.28
102.30	7.29	−0.55	−1.32	−1.63	−0.73	−1.29	0.52	−0.31
40.10	3.30	−0.16	0.44	0.25	0.21	0.18	0.70	0.15
40.50	3.40	−0.23	0.35	0.16	0.14	0.10	0.57	0.07
95.50	5.70	0.66	0.07	−0.23	0.57	0.06	1.53	0.96
35.20	3.17	−0.33	0.33	0.15	0.05	0.06	0.48	−0.05
57.50	3.69	0.51	0.78	0.56	0.78	0.60	1.29	0.86
38.60	3.38	−0.33	0.29	0.10	0.05	0.03	0.52	−0.04
61.50	4.48	−0.05	0.15	−0.09	0.19	−0.02	0.70	0.32
47.40	3.76	−0.17	0.30	0.10	0.17	0.08	0.67	0.18
47.10	3.68	−0.11	0.37	0.16	0.23	0.14	0.86	0.23
44.70	3.26	0.17	0.68	0.48	0.52	0.45	1.09	0.46
52.40	3.99	−0.10	0.28	0.06	0.21	0.08	0.79	0.27
57.90	4.49	−0.27	0.00	−0.23	0.00	−0.18	0.61	0.12
39.50	4.04	−0.93	−0.33	−0.52	−0.56	−0.59	0.00	−0.65
36.70	4.03	−1.09	−0.46	−0.64	−0.72	−0.72	−0.29	−0.82
38.00	3.65	−0.63	−0.01	−0.20	−0.26	−0.28	0.20	−0.35
24.20	2.20	−0.07	0.70	0.55	0.31	0.40	0.38	0.14
17.40	1.80	−0.13	0.66	0.54	0.21	0.34	−0.06	0.02
29.30	2.80	−0.33	0.39	0.23	0.05	0.10	0.27	−0.09
27.00	2.55	−0.23	0.52	0.36	0.15	0.22	0.33	−0.02
32.60	3.21	−0.53	0.16	−0.01	−0.15	−0.12	0.26	−0.26
46.30	5.20	−1.67	−1.19	−1.39	−1.33	−1.41	−0.76	−1.37
35.80	4.30	−1.42	−0.77	−0.95	−1.04	−1.04	−0.57	−1.11
43.10	4.18	−0.85	−0.31	−0.50	−0.49	−0.55	−0.04	−0.51
35.20	3.17	−0.33	0.33	0.15	0.05	0.06	0.48	−0.05
57.50	3.69	0.51	0.78	0.56	0.78	0.60	1.29	0.86
42.80	4.90	−1.59	−1.04	−1.24	−1.23	−1.28	−0.76	−1.26
61.50	4.48	−0.05	0.15	−0.09	0.19	−0.02	0.70	0.32
47.40	3.76	−0.17	0.30	0.10	0.17	0.08	0.67	0.18
47.13	3.68	−0.10	0.37	0.16	0.23	0.14	0.86	0.23
44.73	3.26	0.17	0.69	0.49	0.52	0.45	1.04	0.50

Table 4: Continued.

f_c (MPa)	f_{spt} (MPa)	GEP-III [9]	ACI 363R	ACI 318	CEB-FIP	Regression [9]	RBF	Polynomial
34.60	4.10	−1.30	−0.63	−0.81	−0.91	−0.90	−0.51	−1.02
59.70	5.40	−1.08	−0.84	−1.07	−0.82	−1.01	−0.30	−0.69
51.90	4.00	−0.14	0.25	0.03	0.17	0.04	0.76	0.21
50.00	3.90	−0.15	0.27	0.06	0.17	0.06	0.77	0.22
48.50	4.10	−0.44	0.01	−0.20	−0.11	−0.21	0.49	−0.08
48.80	3.70	−0.02	0.42	0.21	0.31	0.20	0.80	0.32
46.50	3.80	−0.26	0.22	0.02	0.08	−0.01	0.60	0.07
45.20	4.00	−0.54	−0.03	−0.24	−0.19	−0.27	0.30	−0.21
45.20	3.30	0.16	0.67	0.46	0.51	0.43	1.00	0.49
42.60	2.98	0.32	0.87	0.68	0.68	0.63	1.15	0.64
81.60	4.40	1.19	0.93	0.66	1.24	0.86	1.80	1.58
42.70	3.00	0.31	0.86	0.66	0.66	0.61	1.21	0.64
41.90	3.50	−0.24	0.32	0.12	0.12	0.07	0.60	0.09
41.20	3.80	−0.59	−0.01	−0.21	−0.22	−0.26	0.31	−0.26
39.70	2.70	0.42	1.02	0.83	0.79	0.76	1.24	0.73
65.50	5.50	−0.84	−0.73	−0.97	−0.63	−0.87	−0.21	−0.47
39.50	3.70	−0.59	0.01	−0.18	−0.22	−0.25	0.34	−0.31
17.10	1.90	−0.25	0.54	0.42	0.09	0.22	−0.11	−0.10
12.10	1.10	0.18	0.95	0.85	0.48	0.64	0.00	0.31
12.90	1.60	−0.26	0.52	0.41	0.05	0.20	−0.48	−0.13
16.90	1.50	0.13	0.93	0.80	0.48	0.61	0.25	0.28
24.50	2.50	−0.35	0.42	0.27	0.03	0.12	0.16	−0.16

3. SVM for Predicting f_{spt} of Concrete

As mentioned previously, many methods have been proposed for the prediction of f_{spt} from compressive strength of concrete; This study attempts to utilize SVM for the prediction of concrete of f_{spt}. SVM-I model is developed for 150×300 mm cylinder f_{spt} prediction from 150×300 mm cylinder f_c of concrete, and SVM-II model is developed for 100×200 mm and 150×200 mm cylinder f_{spt} prediction from 100×200 mm cylinder f_c of concrete. The experimental data which are taken from studies [9, 14, 15] are used in this study. Among 184 experimental data, 138 data were randomly selected as the training set for SVM-I model and among 168 cases, 126 cases were randomly selected as the training set for SVM-II model, the rest are considered as testing data set. The data are normalized before being used in the model as follows:

$$X = \frac{(X_i - X_{\min})}{(X_{\max} - X_{\min})}, \qquad (16)$$

where $X_{\max}$ and $X_{\min}$ are the maximum and minimum input values data, respectively.

In case of SVM training, two types of kernel functions were used, namely, radical basis function (RBF) and polynomial function, in training process, C and ε and other kernel-specific parameters have been chosen by a trial-and-error approach. The best simulation performances of SVM are summarized in Table 1; in order to evaluate the abilities of SVM models and other models, mean absolute percentage error (MAPE), roof-mean-squared error (RMES), and R-square (R^2) were used as the criteria between the experimental and predicted values, which are, according to the equations,as follow:

$$\text{MAPE} = \frac{1}{n}\left[\frac{\sum_{i=1}^{n}\left|t_i - o_i\right|}{\sum_{i=1}^{n} t_i} \times 100\%\right],$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(t_i - o_i)}, \qquad (17)$$

$$R^2 = \frac{\left(n\sum t_i o_i - \sum t_i \sum o_i\right)^2}{\left(n\sum t_i^2 - \left(\sum t_i^2\right)\right)\left(n\sum o_i^2 - \left(\sum o_i\right)^2\right)},$$

where t_i is the experimental value, o_i is the predicted value and n is total number of data.

4. Results and Discussion

There is no doubt that the splitting tensile strength f_{spt} with an increase in the compression strength of concrete, but there is no agreement on the precise form of the relationship. Codes propose different formulas for prediction cylinder f_{spt} of concrete from compressive strength. In this paper, f_{spt} results are investigated for 150×300 mm cylinder concrete and 100×200 mm cylinder concrete separately. The errors (predicted values subtract measured values) computed by SVM model, other models, and measured values of splitting tensile strengths are shown in Tables 2 and 3 for 150 $\times$ 300 mm cylinder concrete and in Tables 4 and 5 for

Table 5: Comparison of experimental results to testing results of RBF, polynomial of SVM-II, and other models.

f_c (MPa)	f_{spt} (MPa)	GEP-III [9]	ACI 363R	ACI 318	CEB-FIP	Regression	RBF [9]	Polynomial
36.00	3.49	−0.60	0.05	−0.13	−0.22	−0.22	−0.17	−0.04
30.40	3.08	−0.54	0.17	0.01	−0.16	−0.12	−0.10	−0.01
21.60	2.00	−0.04	0.74	0.60	0.33	0.43	0.17	0.34
21.20	2.70	−0.77	0.02	−0.12	−0.40	−0.30	−0.44	−0.39
25.10	2.60	−0.41	0.36	0.21	−0.03	0.05	−0.09	0.06
31.90	3.30	−0.67	0.03	−0.14	−0.28	−0.25	−0.26	−0.12
37.80	3.10	−0.10	0.53	0.34	0.28	0.26	0.48	0.45
29.20	2.50	−0.04	0.69	0.53	0.34	0.40	0.41	0.49
35.40	3.10	−0.25	0.41	0.23	0.13	0.14	0.19	0.32
28.60	3.40	−0.98	−0.24	−0.41	−0.59	−0.54	−0.51	−0.46
29.50	3.10	−0.62	0.10	−0.06	−0.24	−0.19	−0.23	−0.08
34.90	3.50	−0.68	−0.01	−0.19	−0.30	−0.29	−0.23	−0.11
38.60	3.38	−0.33	0.29	0.10	0.05	0.03	0.15	0.23
52.35	3.99	−0.10	0.28	0.06	0.21	0.08	0.42	0.36
38.40	3.80	−0.76	−0.14	−0.33	−0.39	−0.40	−0.23	−0.20
51.50	4.20	−0.36	0.03	−0.18	−0.05	−0.17	0.16	0.11
48.60	4.00	−0.34	0.11	−0.10	0.00	−0.11	0.11	0.16
39.50	3.90	−0.79	−0.19	−0.38	−0.42	−0.45	−0.22	−0.22
30.40	2.85	−0.31	0.40	0.24	0.07	0.11	0.13	0.22
29.50	2.56	−0.08	0.64	0.48	0.30	0.35	0.31	0.46
42.80	4.30	−0.99	−0.44	−0.64	−0.63	−0.68	−0.52	−0.46
51.90	4.30	−0.44	−0.05	−0.27	−0.13	−0.26	0.09	0.03
49.30	4.20	−0.49	−0.06	−0.27	−0.17	−0.27	0.03	0.00
43.30	3.60	−0.26	0.28	0.08	0.10	0.04	0.22	0.28
43.60	3.38	−0.02	0.52	0.32	0.34	0.28	0.46	0.52
49.90	4.57	−0.83	−0.40	−0.61	−0.50	−0.62	−0.34	−0.33
57.40	4.20	−0.01	0.27	0.04	0.26	0.09	0.54	0.39
58.50	4.90	−0.65	−0.39	−0.62	−0.38	−0.56	−0.15	−0.24
31.40	2.79	−0.19	0.52	0.35	0.20	0.23	0.26	0.36
34.90	3.04	−0.22	0.45	0.27	0.16	0.17	0.23	0.35
41.60	3.84	−0.60	−0.03	−0.23	−0.24	−0.28	−0.11	−0.05
46.80	4.00	−0.44	0.04	−0.17	−0.10	−0.19	0.01	0.09
51.70	4.20	−0.35	0.04	−0.17	−0.04	−0.16	0.18	0.12
43.30	3.90	−0.56	−0.02	−0.22	−0.20	−0.26	−0.08	−0.02
60.80	4.10	0.29	0.50	0.27	0.54	0.33	0.76	0.68
60.00	4.30	0.04	0.27	0.04	0.30	0.10	0.60	0.44
71.90	5.40	−0.37	−0.40	−0.65	−0.21	−0.51	0.16	0.00
75.10	5.40	−0.18	−0.29	−0.55	−0.06	−0.39	0.30	0.20
57.87	4.49	−0.27	0.00	−0.23	0.00	−0.18	0.27	0.15
39.50	3.40	−0.29	0.31	0.12	0.08	0.05	0.28	0.28

Table 6: Error measurement for f_{spt} from 150 × 300 mm cylinder f_c.

	GEP-I [9]	ACI 363R	ACI 318	CEB-FIP	Regression [9]	RBF	Polynomial
RMSE of training set	0.4603	0.5995	0.5228	0.5027	0.4512	0.4978	0.4819
RMSE of testing set	0.4271	0.2735	0.3152	0.3754	0.2874	0.2748	0.4176
MAPE of training set	9.7554	13.647	11.4913	10.6213	9.5596	10.2434	10.5454
MAPE of testing set	7.3022	4.6139	5.5434	6.2059	5.286	4.987	6.9517
R^2 of training set	0.8282	0.8225	0.8224	0.8267	0.826	0.8115	0.8227
R^2 of testing set	0.9416	0.9486	0.9486	0.9471	0.9476	0.9422	0.9327

Table 7: Error measurement for f_{spt} from 100 × 200 mm cylinder f_c.

	GEP-III [9]	ACI 363R	ACI 318	CEB-FIP	Regression [9]	RBF	Polynomial
RMSE of training set	0.5886	0.539	0.5244	0.4987	0.4911	0.7287	0.562
RMSE of testing set	0.483	0.3348	0.3393	0.2803	0.3155	0.3082	0.2917
MAPE of training set	11.8729	11.6879	10.9223	9.2976	9.472	15.5902	10.6658
MAPE of testing set	10.8701	7.1383	7.604	6.2261	7.234	6.9713	6.2835
R^2 of training set	0.8198	0.8354	0.8353	0.83	0.8337	0.837	0.8253
R^2 of testing set	0.8778	0.8802	0.8793	0.88	0.8801	0.8815	0.8823

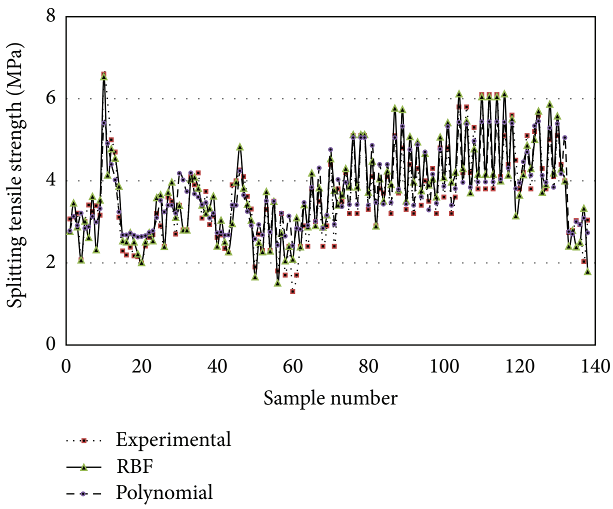

Figure 1: Comparison of experimental results to training results of SVM-I.

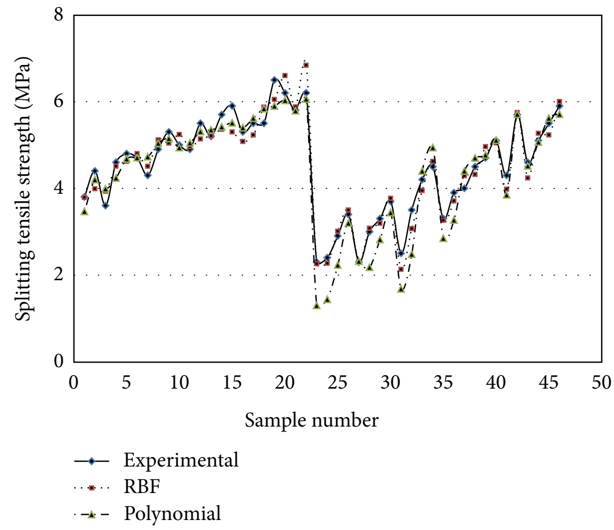

Figure 2: Comparison of experimental results to testing results of SVM-I.

100 × 200 mm cylinder concrete. As seen from these results, SVM model is sufficiently close to the experimental data and is able to predict the f_{spt} from the f_c of concrete. For convenient comparison purpose, the experimental and predicted results are plotted in Figures 1, 2, 3 and 4. It can be seen that the results from SVM method are in good agreement with the experimental results.

The R-square errors in the trained SVM are 0.8115 and 0.8227 for RBF and polynomial function of SVM-I, 0.8370 and 0.8253 for those of SVM-II, respectively. R-square errors in the tested SVM are 0.9422 and 0.9327 for RBF and polynomial function of SVM-I, 0.8815 and 0.8823 for those of SVM-II, respectively. The whole results obtained from the SVM models show a successful performance of the SVM models of predicting 150 × 300 mm cylinder f_{spt} of concrete from the corresponding 150 × 300 mm cylinder compressive strength f_c and 100 × 200 mm cylinder f_{spt} from the corresponding 100 × 200 mm cylinder compressive strength f_c of concrete for each of the training and testing sets. It is also clear that there are no major difference on performance between the radical basis function and the polynomial function kernels that used in this paper. However, in generally, the radical basis function kernel exhibits slightly better performance than the polynomial kernel.

The performance of the trained and tested sets is analyzed by computing MAPE, RMSE and R^2 of experimental f_{spt} between the SVM model and other methods. The MAPE, RMSE, and R^2 are calculated for these methods. Statistical parameters of the training and testing sets of all methods are presented in Tables 6 and 7. The model having the smallest MAPE or RMSE and the highest R^2 can be regarded to be the best model with the assumption of analysis. Generally, R^2 of the SVM models are higher than other methods, and the MAPE and RMSE of SVM are smaller than other models. The analysis shows that the SVM model is better than other models and can predict the splitting tensile strength of concrete well. Furthermore, SVM model has good generalization capacity to avoid over training, and can always be updated to get better results by presenting new training examples as new data become available. Thus, SVM model can be regarded as a very effective method to predict splitting tensile strength of concrete from their compressive strength.

5. Conclusion

The splitting tensile strength of concrete estimations from compression strength has been obtained so far in the literature either through regression or other methods. This present study reports a new and influential approach for predicting the splitting tensile strength using SVM for the first time in the literature. The study conducted in this paper shows

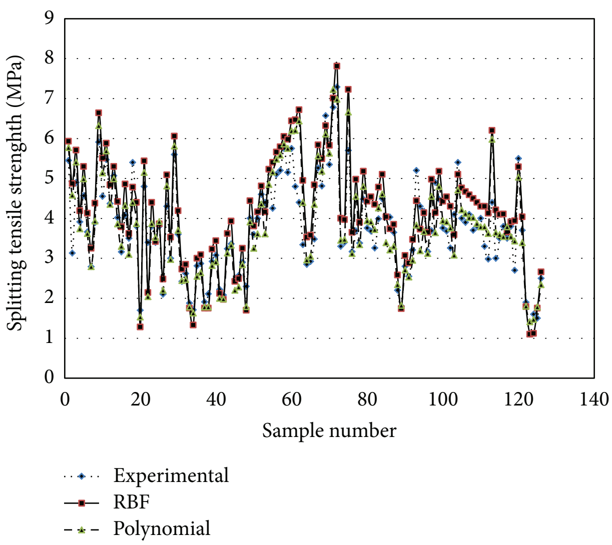

FIGURE 3: Comparison of experimental results to training results of SVM-II.

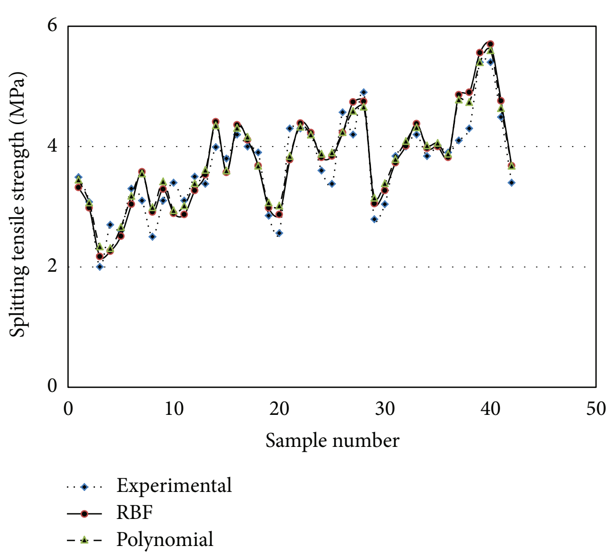

FIGURE 4: Comparison of experimental results to testing results of SVM-II.

the feasibility of using a simple SVM to estimate the splitting tensile strength of concrete. After learning from a set of selected training data, involving compressive strengths of concrete collected from the previous literature, the SVM can be utilized to predict the splitting tensile strengths of the test data.

In this paper, radical basis function and polynomial are adopted for predicting splitting tensile strength from 150 × 300 mm cylinder and 100 × 200 mm cylinder f_c of concrete. It is found that the splitting tensile strength obtained from the SVM is more accurate than those obtained from design codes and several researches' empirical equation when a comparison is made on the basis of the experimental data. Since the SVM is largely characterized by the type of its kernel function, it is necessary to choose the appropriate kernel for each particular application problem in order to guarantee satisfactory results. The results of radial basis function and polynomial indicate that RBF and polynomial kernel have the ability to predict the splitting tensile strength of concrete from compression strength with an acceptable degree of accuracy.

The statistical parameters of MAPE, RMSE, and R^2 show that the proposed SVM model results have the best accuracy and can predict splitting tensile strength very close to experiment results. The use of SVM is very advantageous for the prediction of the splitting tensile strength of concrete from compression strength because it can perform nonlinear regression efficiently for high-dimensional data sets. Furthermore, its solution is global. The satisfactory predictions of the splitting tensile strength of concrete by the model indicate that SVM is a useful modeling tool for engineers and research scientists at concrete construction fields.

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References

[1] B. W. Xu and H. S. Shi, "Correlations among mechanical properties of steel fiber reinforced concrete," *Construction and Building Materials*, vol. 23, no. 12, pp. 3468–3474, 2009.

[2] M. F. M. Zain, H. B. Mahmud, A. Ilham, and M. Faizal, "Prediction of splitting tensile strength of high-performance concrete," *Cement and Concrete Research*, vol. 32, no. 8, pp. 1251–1258, 2002.

[3] F. A. Oluokun, E. G. Burdette, and J. H. Deatherage, "Splitting tensile strength and compressive strength relationship at early ages," *ACI Materials Journal*, vol. 88, no. 2, pp. 115–121, 1991.

[4] Y. Choi and R. L. Yuan, "Experimental relationship between splitting tensile strength and compressive strength of GFRC and PFRC," *Cement and Concrete Research*, vol. 35, no. 8, pp. 1587–1591, 2005.

[5] F. D. Larrad and Y. Malier, "Engineering properties of very high performance concrete," in *High Performance Concrete, from Material to Structure*, Y. Malier, Ed., pp. 85–114, EFN Spon, London, UK, 1992.

[6] J. K. Kim, S. H. Han, Y. D. Park, and J. H. Noh, "Material properties of self-flowing concrete," *Journal of Materials in Civil Engineering*, vol. 10, no. 4, pp. 244–249, 1998.

[7] J. K. Kim, S. H. Han, and Y. C. Song, "Effect of temperature and aging on the mechanical properties of concrete—part I: experimental results," *Cement and Concrete Research*, vol. 32, no. 7, pp. 1087–1094, 2002.

[8] A. M. Shaaban and H. Gesund, "Splitting tensile strength of steel fiber reinforced concrete cylinders consolidated by rodding or vibrating," *ACI Materials Journal*, vol. 90, no. 4, pp. 366–369, 1993.

[9] M. Saridemir, "Empirical modeling of splitting tensile strength from cylinder compressive strength of concrete by genetic programming," *Expert Systems with Applications*, vol. 38, no. 11, pp. 14257–14268, 2011.

[10] U. Thissen, R. van Brakel, A. P. de Weijer, W. J. Melssen, and L. M. C. Buydens, "Using support vector machines for time series prediction," *Chemometrics and Intelligent Laboratory Systems*, vol. 69, no. 1-2, pp. 35–49, 2003.

[11] P. Samui, "Predicted ultimate capacity of laterally loaded piles in clay using support vector machine," *Geomechanics and Geoengineering*, vol. 3, no. 2, pp. 113–120, 2008.

[12] V. N. Vapnik, *The Nature of Statistical Learning Theory*, Springer, New York, NY, USA, 1995.

[13] V. N. Vapnik, S. E. Golowich, and A. J. Smola, "Support vector machine for function approximation, regression estimation, and signal processing," *Advances in Neural Information Processing Systems*, vol. 9, pp. 281–287, 1996.

[14] M. Khanzadi and A. Behnood, "Mechanical properties of high-strength concrete incorporating copper slag as coarse aggregate," *Construction and Building Materials*, vol. 23, no. 6, pp. 2183–2188, 2009.

[15] C. K. Y. Leung and J. Pan, "Effect of concrete composition on FRP/concrete bond capacity," in *Proceedings of the International Symposium on Bond Behaviour of FRP in Structures (BBFS '05)*, pp. 69–76, 2005.