Prediction of Compressive, Flexural and Splitting Tensile Strengths of Concrete using Machine Learning Tools

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***Abstract*- This paper deals with the application of Support Vector Machine Technique (SVM) and Artificial Neural Network (ANN) for predicting compressive, flexural and splitting tensile strengths of concrete. Using the SVM technique and the experimental test data available in the literature, three equations have been developed for the compressive, flexural and splitting tensile strengths of concrete. Further, 27 concrete cubes, 27 concrete cylinders and 27 concrete beams were cast and tested for compressive, splitting tensile and flexural strengths of concrete in the present work. The experimental results so obtained are compared with those given by the developed equations. The main parameters considered in the equations are: quantities of cement, fly ash, super-plasticizer, fine aggregate, coarse aggregate, water and age in days. It is seen that the discrepancy between the experimental results and those obtained by using SVM ranged from 1 to 35%. It is also seen that the discrepancy between the experimental results and those obtained by using ANN ranged from 1 to 50%. The flexural strength results given by SVM are closer to the experimental values than those given by ANN in all the cases. The compressive and splitting tensile strength results given by SVM are closer to the experimental values than those given by ANN in 52% and 67% of the cases considered here.**

Keywords— Compressive Strength, Flexural Strength, Splitting Tensile Strength, Support Vector Machine Technique (SVM), Artificial Neural Network (ANN)

I. INTRODUCTION

Concretes have wide application in civil engineering field. The mechanical properties of concrete such as compressive strength, flexural strength and splitting tensile strength are of vital importance in the analysis and design of concrete structures. These mechanical properties can be predicted using machine learning tools. Machine learning is a scientific discipline that explores the construction and study of algorithms that can learn from data. Such algorithms operate by building a model based on inputs and using them to make predictions or decisions, rather than following only explicitly programmed instructions. The present study is carried out to develop equations for the aforesaid mechanical properties of concrete using SVM and the experimental data available in literature. Then the values given by the equations are compared with the results of experiments carried out on concrete in the present work. A comparison is made between the results given by SVM and ANN relative to the experimental values. References [1] through [11] deal with machine learning tools. The other references deal with the experimental studies on concrete. Reference [29] mentions some of the applications of SVM to concrete in the context of civil engineering.

II. SUPPORT VECTOR MACHINE TECHNIQUE

A. Introduction

SVM is one of the machine learning techniques (MLT) derived from statistical learning theory by Vapnik and Chervonenkis in 1964. The foundations of SVM have been developed by Vapnik (1995) at AT&T Bell Laboratories. SVM is recognized as an attractive and promising tool to solve classification and regression related problems (Gunn 1998). Initially, SVM as a classifier focused on optical character recognition and object recognition tasks. SVM has also excelled in regression and time series prediction applications. Compared to regression methods by conventional ANN, SVM in regression approximation has three distinct characteristics as follows:

- SVM uses a set of linear functions defined in a high dimensional space.
- SVM carries out risk minimization using loss functions.
- SVM uses a risk function consisting of empirical error and a regularization term which is derived from the support regression method.

The main idea of SVM is to transform the input space into a high-dimensional space. 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 network which is based on the traditional minimization principle of experience risk. 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. 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 empirical error and a regularization term which is derived from the structural risk minimization (SRM) principle.

B. WEKA Software

Weka software is based on SVM technique. It processes a collection of machine learning algorithms for data mining and machine learning tasks, feature selection, classification, regression, clustering, association rules and visualization. Using this software equations for the compressive, flexural and splitting tensile strengths of concrete are developed considering the following parameters: quantities of cement, fly ash, super plasticiser, fine aggregate, coarse aggregate, water and age in days.

1) Following relation has been obtained for predicting the compressive strength:

P_{com} = 0.0783 *cement + 0.0456 * fly ash - 0.153 *SP + 0.0094*fine aggregate + 0.0122 *coarse aggregate + 0.034 *water + 0.0291 *age – 25.975 ...... (1)

2) Following relation has been obtained for predicting the flexural strength:

P_{flex} = 0.0032*cement - 0.0005* fly ash - 0.0645* SP - 0.0017* fine aggregate + 0.0033*coarse aggregate - 0.0264 * water + 0.0022 * age + 4.1987 …….. (2)

3) Following relation has been obtained for predicting the splitting tensile strength:

P_{split} = 0.0118*cement - 0.0042* fly ash - 0.1923* SP - 0.0005* fine aggregate + 0.0054*coarse aggregate - 0.0012 * water + 0.0015 * age + 6.3142 …… (3)

The strengths predicted by using SVM in respect of cubes, cylinders and beams tested in the present work are tabulated in Table 1 through 3 along with other relevant results.

III.ARTIFICIAL NEURAL NETWORK

ANN has emerged as a useful concept from the field of artificial intelligence and has been successful over the past decade in modeling engineering problems.
ANN generally consists of a number of layers. The layer where the patterns are applied is called input layer. This layer could include the parameters of concrete such as: quantities of cement, fly ash, super plasticizer, fine aggregate, coarse aggregate, water and age in days. The layer where the output is obtained is the output layer. In addition, there may be one or more layers between input and output, called hidden layers which are so named because their outputs are not directly observed. The addition of hidden layers enables the network to extract higher order statistics which are particularly valuable when the size of input is very large. Neurons in each layer are interconnected to neurons of subsequent layer.

Neuron Model

The experimental data available in literature were taken for neural network training. The software employed is Alyuda Neuro Intelligence. The percentage of data used for training is 68.33%. The percentage of data used for validation is 15.83%. The percentage of data used for testing is 15.83%. To train the model 7 different network architectures were considered. The number of hidden layers was varied from 1 - 25. The 7 networks were auto-verified by the software. The architecture selected for training is [7-3-1] which is shown in Fig.1.

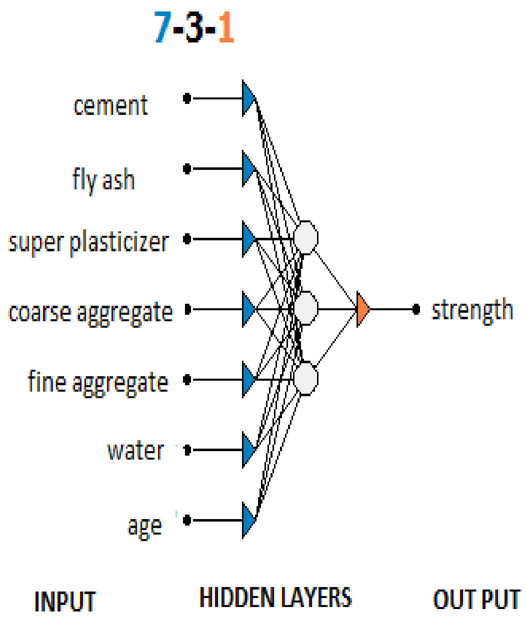

Fig.1: ANN Model

The strengths predicted by using Artificial Neural Network in respect of cubes, cylinders and beams tested in the present work are tabulated in Table 1 through 3 along with other relevant results. The work flow chart is shown in Fig.2.

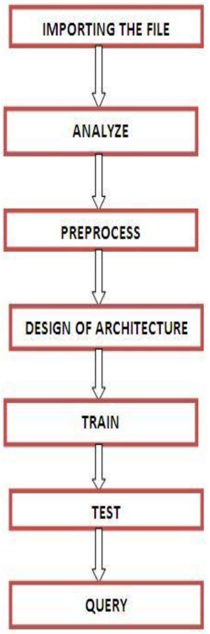

Fig.2: Work Flow Chart

Table 1: Experimental, SVM and ANN Values of Compressive Strength

Cube Mark	Compressive Strength (MPa)				SVM ERROR (%)	ANN ERROR (%)
	Age (days)	EXP	SVM	ANN		
A1	7	17.80	22.76	26.25	27.87	47.49
A2	7	17.90	22.76	26.25	27.15	46.66
A3	7	17.50	22.76	26.25	30.06	50.01
A4	14	19.80	24.80	26.25	25.25	32.60
A5	14	19.60	24.80	26.25	26.53	33.95
A6	14	19.50	24.80	26.25	27.18	34.64
A7	28	27.30	28.87	26.27	5.75	3.76
A8	28	27.90	28.87	26.27	3.48	5.83
A9	28	27.70	28.87	26.27	4.22	5.15
A10	7	19.70	26.03	26.30	32.13	33.48
A11	7	20.10	26.03	26.30	29.50	30.83
A12	7	20.70	26.03	26.30	25.75	27.03
A13	14	22.30	28.06	26.39	25.83	18.35
A14	14	23.40	28.06	26.39	19.91	12.79
A15	14	23.70	28.06	26.39	18.40	11.36
A16	28	31.20	32.14	27.67	3.01	11.31
A17	28	32.30	32.14	27.67	0.50	14.33
A18	28	31.60	32.14	27.67	1.71	12.44
A19	7	20.10	27.10	26.47	34.83	31.69
A20	7	20.90	27.10	26.47	29.67	26.65
A21	7	20.80	27.10	26.47	30.29	27.25
A22	14	24.90	29.13	26.94	16.99	8.20
A23	14	24.30	29.13	26.94	19.88	10.87
A24	14	24.60	29.13	26.94	18.41	9.52
A25	28	32.40	33.21	32.44	2.50	0.12
A26	28	32.70	33.21	32.44	1.56	0.80
A27	28	32.80	33.21	32.44	1.25	1.10

Table 2: Experimental, SVM and ANN Values of Flexural Strength

Beam Mark	Flexural Strength (MPa)				SVM ERROR (%)	ANN ERROR (%)
	Age (days)	EXP	SVM	ANN		
B1	7	2.48	2.58	3.39	4.03	36.73
B2	7	2.53	2.58	3.39	1.98	34.03
B3	7	2.61	2.58	3.39	1.15	29.92
B4	14	2.69	2.59	3.39	3.72	25.92
B5	14	2.51	2.59	3.39	3.19	34.95
B6	14	2.56	2.59	3.39	1.17	32.32
B7	28	2.58	2.61	3.38	1.16	31.02
B8	28	2.68	2.61	3.38	2.61	26.14
B9	28	2.66	2.61	3.38	1.88	27.08
B10	7	2.92	2.96	3.42	1.37	16.98
B11	7	2.85	2.96	3.42	3.86	19.86
B12	7	2.89	2.96	3.42	2.42	18.20
B13	14	2.97	2.97	3.41	0.00	14.83
B14	14	2.88	2.97	3.41	3.13	18.42
B15	14	2.94	2.97	3.41	1.02	16.00
B16	28	2.87	2.99	3.40	4.18	18.47
B17	28	2.83	2.99	3.40	5.65	20.14
B18	28	2.97	2.99	3.40	0.67	14.48
B19	7	2.99	3.26	3.54	9.03	18.55
B20	7	3.12	3.26	3.54	4.49	13.61
B21	7	3.09	3.26	3.54	5.50	14.71
B22	14	3.22	3.27	3.53	1.55	9.76
B23	14	3.37	3.27	3.53	2.97	4.87
B24	14	3.33	3.27	3.53	1.80	6.13
B25	28	3.19	3.29	3.51	3.13	10.17
B26	28	3.11	3.29	3.51	5.79	13.01
B27	28	3.21	3.29	3.51	2.49	9.48

Table 3: Experimental, SVM and ANN Values of Splitting Tensile Strength

Cyl Mark	Splitting Tensile Strength (MPa)				SVM ERROR (%)	ANN ERROR (%)
	Age (days)	EXP	SVM	ANN		
C1	7	2.07	2.15	2.94	4.07	42.20
C2	7	2.02	2.15	2.94	6.65	45.72
C3	7	2.15	2.15	2.94	0.20	36.91
C4	14	2.21	2.17	2.94	1.82	33.23
C5	14	2.24	2.17	2.94	3.14	31.44
C6	14	2.07	2.17	2.94	4.82	42.24
C7	28	2.09	2.20	2.95	5.29	40.96
C8	28	2.19	2.20	2.95	0.48	34.53
C9	28	2.28	2.20	2.95	3.48	29.22
C10	7	2.64	2.41	2.95	8.53	11.80
C11	7	2.73	2.41	2.95	11.55	8.12
C12	7	2.48	2.41	2.95	2.63	19.02

C13	14	2.79	2.43	2.95	12.90	5.87
C14	14	2.81	2.43	2.95	13.52	5.12
C15	14	2.88	2.43	2.95	15.62	2.56
C16	28	2.78	2.46	2.96	11.48	6.45
C17	28	2.96	2.46	2.96	16.86	0.02
C18	28	2.31	2.46	2.96	6.53	28.11
C19	7	2.23	2.74	2.98	23.03	33.51
C20	7	2.07	2.74	2.98	32.54	43.83
C21	7	2.98	2.74	2.98	7.93	0.09
C22	14	3.11	2.76	2.98	11.29	4.05
C23	14	2.18	2.76	2.98	26.56	36.88
C24	14	3.18	2.76	2.98	13.24	6.16
C25	28	2.35	2.79	3.00	18.71	27.73
C26	28	2.34	2.79	3.00	19.22	28.27
C27	28	3.25	2.79	3.00	14.16	7.64

IV. EXPERIMENTAL WORK

A. Concrete Properties

27 no. of concrete cubes of size 150mm X 150mm X 150mm and 27 no of 150mm diameter and 300mm height concrete cylinders and concrete beams of size 100mm X 80mm X 700mm were cast and tested. Concrete cubes A1 to A9 and cylinders C1 to C9 and Beams B1 to B9 were cast using a proportion of 0.6 (Cement): 0.4 (fly ash): 2.54 (Sand): 3.82 (Coarse Aggregate) with a water-cement ratio of 0.52. Concrete cubes A10 to A18 and cylinders C10 to C18 and Beams B10 to B18 were cast using a proportion of 0.7 (Cement): 0.3 (fly ash): 2.54 (Sand): 3.82 (Coarse Aggregate) with a water-cement ratio of 0.45. Concrete cubes A19 to A27 and cylinders C19 to C27 and Beams B19 to B27 were cast using a proportion of 0.8 (Cement): 0.2 (fly ash): 2.54 (Sand): 3.82 (Coarse Aggregate) with a water-cement ratio of 0.43. Ordinary Portland cement of grade 53 was used for all the specimens. Natural river sand conforming to Zone II was used for all the specimens.

V. DISCUSSION OF RESULTS

From Table 1, the following are observed in respect of compressive strength of concrete:

- SVM predicts the 28 days strength with an error of 1 to 6%.
- SVM predicts the 14 days strength with an error ranging from 16 to 27%.
- SVM predicts the 7 days strength with an error ranging from 26 to 35%.
- ANN predicts the 28 days strength with an error of 0 to 15%.
- ANN predicts the 14 days strength with an error ranging from 8 to 35%.
- ANN predicts the 7 days strength with an error ranging from 27 to 50%.

From Table 2, the following are observed in respect of flexural strength of concrete:

- SVM predicts the 28 days strength with an error of 0 to 6%.
- SVM predicts the 14 days strength with an error ranging from 0 to 5%.
- SVM predicts the 7 days strength with an error ranging from 1 to 9%.
- ANN predicts the 28 days strength with an error of 10 to 31%.
- ANN predicts the 14 days strength with an error ranging from 4 to 35%.
- ANN predicts the 7 days strength with an error ranging from 13 to 37%.

From Table 3, the following are observed in respect of splitting tensile strength of concrete:

- SVM predicts the 28 days strength with an error of 0 to 20%.
- SVM predicts the 14 days strength with an error ranging from 1 to 27%.
- SVM predicts the 7 days strength with an error ranging from 0 to 33%.
- ANN predicts the 28 days strength with an error of 0 to 41%.
- ANN predicts the 14 days strength with an error ranging from 2 to 43%.
- ANN predicts the 7 days strength with an error ranging from 0 to 46%.

VI. CONCLUSIONS

Based on the above study the following conclusions are made:

- ➢ Using SVM technique equations have been developed for predicting the compressive strength, flexural strength and splitting tensile strength of concrete considering the available literature data.
- ➢ The machine learning tool SVM predicts the 28 days compressive strength of concrete quite accurately (discrepancy varying from 1 to 6%). The ANN is also observed to predict the 28 days compressive strength reasonably well (0 to 15%). The accuracy with which SVM and ANN predict the 7days and 14 days compressive strength is not high.
- ➢ The machine learning tool SVM predicts the 28 days flexural strength of concrete quite accurately (discrepancy varying from 0 to 6%). The ANN is observed to predict the 28 days flexural strength with less accuracy. The accuracy with which SVM predicts the 7days and 14 days flexural strength is quite good (0 to 9%). The accuracy with which ANN predicts the 7days and 14 days flexural strength is not high.

- The machine learning tool SVM predicts the 7 days, 14 days and 28 days splitting tensile strength of concrete with an accuracy ranging from high to moderate. The ANN predicts the 7 days, 14 days and 28 days splitting tensile strength of concrete with an accuracy ranging from high to low.
- SVM is seen to predict the experimental values better than ANN in more number of cases and holds great promise as a better predicting tool.

ACKNOWLEDGEMENT

The first, the third and the last authors gratefully acknowledge the encouragement and support provided by the Management, Principal and Head of the Department of Civil Engineering Dr. Y. Ramalinga Reddy, Reva Institute of Technology and Management, Bengaluru 560 064. The second author gratefully acknowledges the encouragement and support provided by the Management, Principal and HOD (Civil) of Sir M Visvesvaraya Institute of Technology, Bengaluru 560 064.

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