ESTIMATION OF COMPRESSIVE STRENGTH OF PUMPABLE CONCRETE USING MACHINE LEARNING TECHNIQUE

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ABSTRACT. Pumpable concrete is conveyed under pressure through a hose or a pipe. Now-a-days it is widely used in infrastructure construction practices as it saves labour, cost and time. The compressive strength of concrete at 28 days is a commonly used criterion in producing concrete. The tests on the compressive strength are complicated and time consuming. Sometimes, it is too late to make improvements even if the test result does not satisfy the required strength, since the test is usually performed on the 28th day after the placement of concrete at the construction site. Early prediction or estimation of compressive strength is necessary to assure the target strength of it. Conventional methods for predicting 28-days compressive strength of concrete are based on statistical analyses, by which many linear and nonlinear regression equations have been constructed to model such prediction problems. Different machine learning techniques can be used to predict the compressive strength of concrete and have become an important research area. Support vector machine is an advanced method of machine learning techniques. The objective of this study is to apply support vector machine technique for estimation of compressive strength of pumpable concrete. The study contained the trial mixes for pumpable concrete designed as per IS 10262: 2009 in the laboratory. Sufficient numbers of trial data are used with wide range of water/cement ratios with slump more than 100 mm and strength of M25, M30 and M35 grade of concrete. This study demonstrates that support vector machine method is an effective technique to estimate the compressive strength of it. This study can help to predict the compressive strength of pumpable concrete before its placement. It will reduce the number of trials, and save cost, labour and time.

Keywords: Machine learning techniques, Support vector machine, Pumpable concrete, Compressive strength, Paste content

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INTRODUCTION

Concrete is the most widely used construction material in the world. The composite material of concrete is obtained by mixing cement, water and aggregates. The strength, durability and other characteristics of concrete depend upon the properties of its ingredients, the proportions of the mix, the method of compaction and other controls. Among the various properties of concrete, its compressive strength is considered to be the most important.

The compressive strength of concrete is known as the most important mechanical property which is generally obtained by measuring concrete specimen’s strength after a standard curing of 28 days [1]. The compressive strength prediction creates a high degree of complexity and uncertainty due to the variable nature of constituent materials, workmanship quality, etc. One of the main parameters that affect the compressive strength is the w/c ratio (as given by Abram’s law) [2], other parameters are less considered. Linear or nonlinear regression models are usually utilized to predict the compressive strength of concrete [1, 3]. But, in most cases these methods fail to meet the extrapolation accuracy and generalization requirements. Recently, artificial intelligence-based systems have been successfully implemented in this area like artificial neural networks [4, 5], probabilistic neural networks [6], neuro-fuzzy polynomials [7] etc. Among these methods, support vector machine based on the structural risk minimization principle [3, 8], is one of the promising method for modelling and prediction of concrete's compressive strength. This method is successfully applied in field of predicting the fracture parameters of concrete [9], compressive strength of no-slump concrete [3], nonlinear structural response[10], elastic modulus of normal and high strength concrete [11], field hydraulic conductivity of sandy soil [12] and construction management [11, 13].

This paper focuses on the prediction of the 28-days compressive strength of pumpable concrete using support vector machine (SVMs). Pumpable concrete is defined as concrete that is conveyed under pressure through either rigid pipe or flexible hose and discharged directly into the desired location. It is made in such a manner that its friction at the inner wall of the pipeline does not become very high and it does not wedge while flowing through the pipeline. Indian standard (IS:10262-2009) [14] defines pumpable concrete as concrete having slumps above 75 mm whereas American concrete institute (ACI) [15] defines it as concrete that is transported through hose or pipe by means of a pump. The physical properties of pumpable concrete, specifically the compressive strength, are very sensitive to its ingredients and mix proportions. So, predicting the compressive strength of pumpable concrete is a highly complicated problem that requires more accurate and reliable methods for predicting it.

SUPPORT VECTOR MACHINE

In machine learning, support vector machines (SVMs) are supervised learning models with associated learning algorithms that analyze data used for classification and regression analysis. With a given a set of training patterns, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces.

Linear SVM: It is the newest extremely fast machine learning algorithm for solving multiclass classification problems from ultra large data sets that implements an original proprietary version of a cutting plane algorithm for designing a linear support vector machine. A training dataset of points are given in the form $(x_1,y_1),.....(x_i, y_i)....,(x_n,y_n)$.
Where the y_i is either 1 or −1, each indicating the class to which the point x_i belongs. Each x_i is a p-dimensional real vector. We want to find the "maximum-margin hyperplane" that divides the group of points x_i for $y_i= -1$. It is defined such that the distance between the hyperplane and the nearest point x_i from either group is maximized.
Any hyperplane can be written as the set of points x satisfying $w.x - b = 0$,as shown in figure 1, where w is the normal vector to the hyperplane.

Non-Linear SVM: The nonlinear classifiers are proposed by Bernhard E. Boser, Isabelle M. Guyonand, Vladimir N. Vapnik in 1992 [16] by applying the kernel trick to maximum-margin hyperplanes. Some important kernel functions are given in table 1 [17]. The resulting algorithm is formally similar, except that every dot product is replaced by a nonlinear kernel function. This allows the algorithm to fit the maximum-margin hyperplane in a transformed feature space. Figure 2 shows a clear image of non-linear SVM.

Kernel trick: Suppose we would like to learn a non linear classification rule corresponds to a linear classification rule for the transformed data points $\varphi(x_i)$. The steps are stated in equations (1) to (4). A kernel function k should satisfy

$$k(x_i, x_j) = \varphi(x_i).\varphi(x_j).c_i y_i x_i \tag{1}$$

The classification vector w in the transform space satisfies

$$w = \sum_{i=1}^{n} c_i y_i \varphi(x_i), \tag{2}$$

Where c_i are obtained by solving the optimization problem

$$\text{Maximize} f(c_1 \dots c_n) = \sum_{i=1}^{n} c_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} c_i y_i(\varphi(x_i).\varphi(x_j))y_i c_j \tag{3}$$

$$= \sum_{i=1}^{n} c_i - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n} y_i c_i k(x_i, x_j) y_i c_j \tag{4}$$

Subject to $\sum_{i=1}^{n} c_i y_i = 0$, and $0 \le c_i \le \frac{1}{2\lambda}$ for all i.

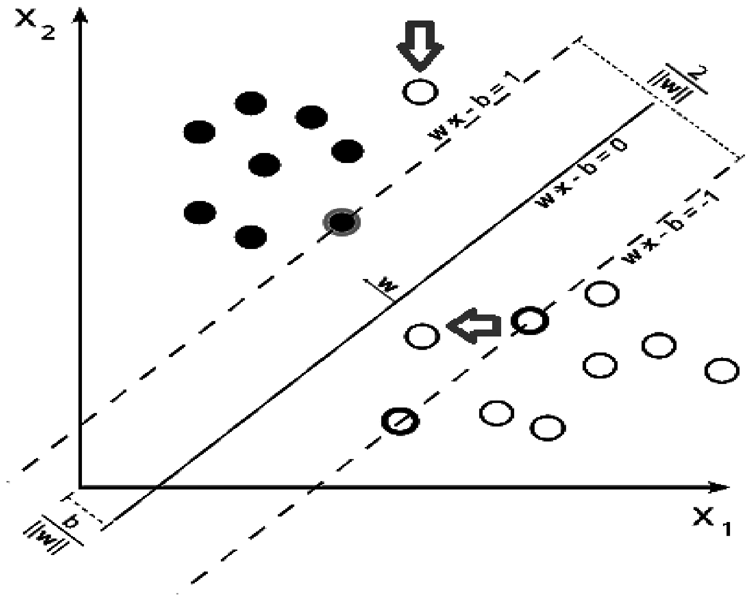

Figure 1 Linear SVM

Table1 Different types of kernel functions

TYPES OF CLASSIFICATION	KERNEL FUNCTIONS
Polynomial Kernel	$k(x_i, x_j) = (x_i . x_j + 1)^d$
Gaussian kernel	$k(x, y) = exp(-\frac{\|\|x-y\|\|2}{2\sigma 2})$
Gaussian radial basis function	$k(x_i, x_j) = \exp(-\gamma \|\|x_i - x_j\|\|^2)$
Laplace RBF kernel	$k(x, y) = exp(-\frac{\|\|x-y\|\|}{\sigma})$
Hyperbolic tangent kernel	$k(x_i, x_j) = tanh(kx_i, x_j + c)$
Sigmoid kernel	$k(x, y) = tanh(\alpha x^t y + c)$
ANOVA radial basis kernel	$k(x, y) = \sum_{k=1}^{n} exp(-\sigma(x^k - y^k)^2)^d$

LITERATURE REVIEW

The compressive strength of pumpable concrete is a very significant property once the flow of concrete in the pipe is established. However, no universal theory exits for the relation between compressive strength and the composition of concrete except the Abram's law [2]. Many studies are done to predict the 28-day compressive strength.

Sobhani, Khanzadi and Movahedian [3] proposed the use of support vector machine for the prediction of compressive strength of no slump concrete. The input parameters used are cement, silica fumes, water, fine aggregate, coarse aggregate and filler if any. The output parameter was the compressive strength of no slump concrete.

Samui and Kim [9] utilized SVM for prediction of fracture parameters of concretefollowing the TPM approach which is based on the critical stress intensity factor and the critical crack tip opening displacement (CTODc) as fracture parameters.

Yan and Shi [11] proposed the use of support vector machine for the prediction of elastic modulus of normal and high strength concrete. In this, compressive strength was considered as the input parameter in SVM model and the output is elastic modulus.

Hoon, Park, Kang and Cho [18] utilized SVM in assessing conceptual cost estimates. They assessed the conceptual cost estimate was by using the one-versus-rest (OVR) method in which one class is separated from the remaining classes in the SVM model.

Pal and Deswal [19] proposed support vector regression for shear strength modelling of reinforced and prestressed concrete deep beams. The input parameter includes ratio of effective span to effective depth of beams, concrete cylinder strength, ratio of effective depth to breadth of beam, ratio of shear span to effective depth of beam, yield strength of horizontal reinforcement, yield strength of vertical web reinforcement, ratio of horizontal web reinforcement, ratio of longitudinal reinforcement to area of concrete and ratio of vertical web reinforcement. The output parameter was shear strength.

Gryllias and Antoniadis [20] used SVM for rolling element bearing fault detection in industrial environments. Since, an unexpected failure of machine can lead to unacceptably long time maintenance stops. Thus, due to their importance, fault diagnosis procedures have been developed for rolling element bearings.

From the literature review, it is understood that SVM is an efficient and accepted technique in different civil engineering problems. In this paper, SVM is used for predicting compressive strength of pumpable concrete.

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DATA COLLECTION AND METHODOLOGY

The data is collected from the experimental study in our laboratory on mix designing of pumpable concrete [21]. The work contains a total of 86 trail mixes at different water cement ratios ranging from 0.38 to 0.48 with the variation of 0.01 and water reduction was varied from 8% to 25%. It contains three grades of concreteM25, M30 and M35. Super plasticizer was added to get 125 mm slump which is the requirement of pumpable concrete. All the mix design was performed under the guidelines of IS:10262-2009 [14]. Three different types of super plasticizers were used in the mixes. First one is chemical base sulphonated naphthalene polymers with water reduction capacity of 16-25%, second and third are based on modified lingo sulphate with water reduction capacity of 5-10% and 10-18% respectively. The slump of the mixes was tested using the slump cone test and compressive strength was measured using 15cm cubes after 28 days. The all input and output data are given in table 2.

In this study, the parameters that are considered for estimation of compressive strength are w/c ratio, water reduction (%), slump (mm), cement content (kg/m^3), water content (kg/m^3), FA/TA ratio, C/TA ratio, super plasticizer content (kg/m^3) and the real paste content (%). The systematic structure of SVM model is given in figure 3.

Table 2 Range of input and output parameters used for training the network

	PARAMETERS	MINIMIUM VALUE	MAXIMUM VALUE
Inputs	W/C ratio	0.38	0.48
	Water reduction (%)	8	24
	Slump(mm)	118	135
	Cement content(kg/m^3)	375.8	449.97
	Water content(kg/m^3)	154.08	186.52
	FA/TA ratio	0.412	0.431
	C/TA ratio	0.195	0.252
	Superplasticizers (kg/m^3)	1.52	5.1
	Paste content(%)	27.73	33.04
Output	Compressive strength(MPa)	27.03	43.89

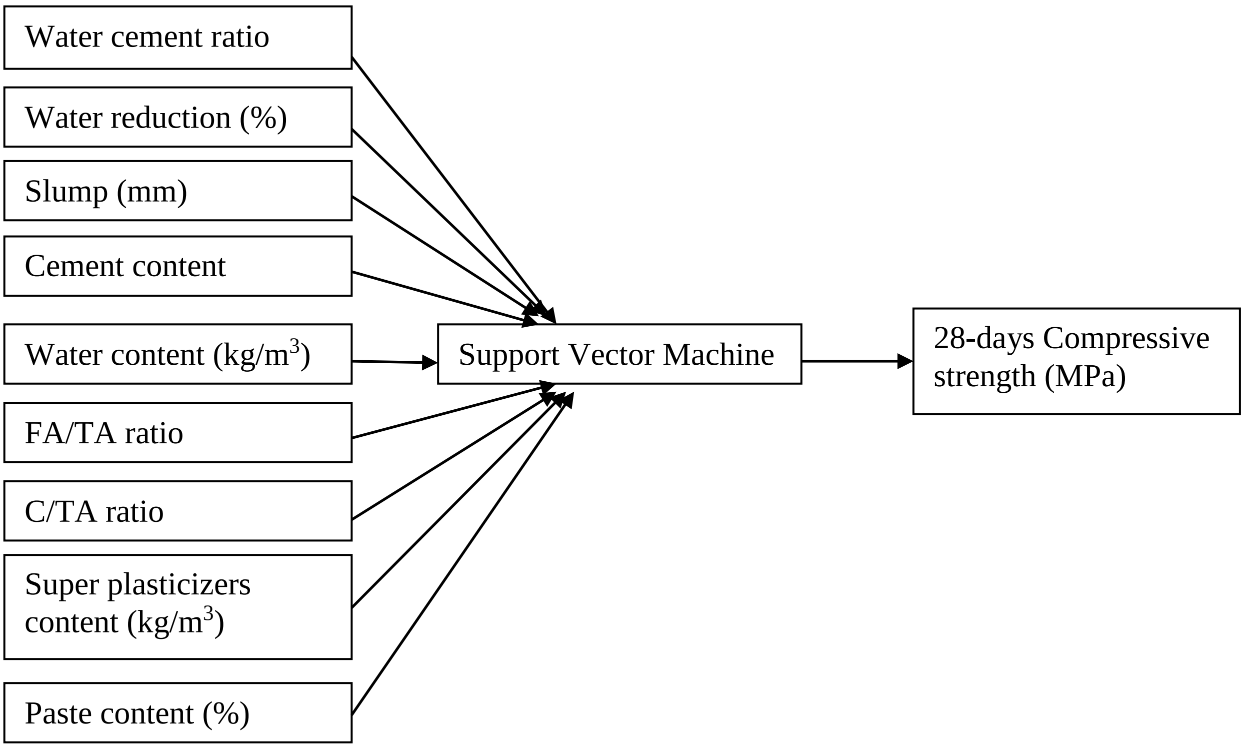


Figure 3 The systematic structure of SVM

RESULTS AND DISCUSSION

To evaluate the performances of the given model, the indexes mean square error (MSE), mean absolute error (MAE) and correlation coefficient (R) were used. MSE, MAE and R values are calculated by using equations (5), (6) and (7) respectively.

$$MSE = \sqrt{\frac{\sum_{i=1}^{n}(Y_i^{model} - Y_i^{real})^2}{n}} \quad (5)$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|Y_i^{model} - Y_i^{real}| \quad (6)$$

$$R = \frac{N\sum Y_i^{model}Y_i^{real} - (\sum Y_i^{model})(\sum Y_i^{real})}{\sqrt{[N\sum Y_i^{model^2} - (\sum Y_i^{model})^2[N\sum Y_i^{real^2} - (\sum Y_i^{real})^2]]}} \quad (7)$$

Where Y_i^{model} is real output and Y_i^{real} is predictive output and n is the number of samples.

Modelling with SVM

The tuning of SVM parameters is a heuristic process. Gaussian kernel function was used in proposed model to give more accurate results. Linear, quadratic and cubic kernel can also be used but they are less accurate as compared to Gaussian kernel. This case has taken 76 data as training and 10 data as testing parameters. For the given training data, linear kernel gives only 53.9% accuracy while quadratic kernel gives 69.7% accuracy whereas cubic kernel gives 92.1% accuracy but with Gaussian kernel, it gives 95.4% accuracy. So, Gaussian kernel function is the best suitable for the given data. Similarly, for testing data also Gaussian kernel gives best result with 99.6% accuracy. In all cases, computational software and its corresponding classification learner toolbox utilized to construct and training the SVM models respectively. The fitness function was chosen as root mean square (RMS) error technique. Table 3 shows the output results of training and testing data of SVM.

Table 3 SVM models results for training and testing datasets

SVM models	σ	η	b	N_{sv}	MSE	R	E
Training	4.77	35.27	-0.1034	76	0.2499	0.9977	0.9954
Testing	2.95	30.71	0.0023	10	0.00053	0.9999	0.9990

Note: σ = width of radial kernel function (sigma), η = Mu, b = bias of SVM, N_{sv}= number of support vectors, MSE = mean square error, R = correlation coefficient, E = coefficient of determination, Total runtime = 45 sec

* For all of optimizations PC with 3.1 GHz Core i5 7th generation CPU and 8 GB Ram was used

● Bias (b) = It indicates a special parameters in SVM($w.x - b = 0$, where '*b*' is the bias). Without it the classifier will always pass through origin. So, SVM does not give separately hyper plane with maximum margin unless have a bias term.

● Sigma (σ) = Sigma is usually a standard deviation.

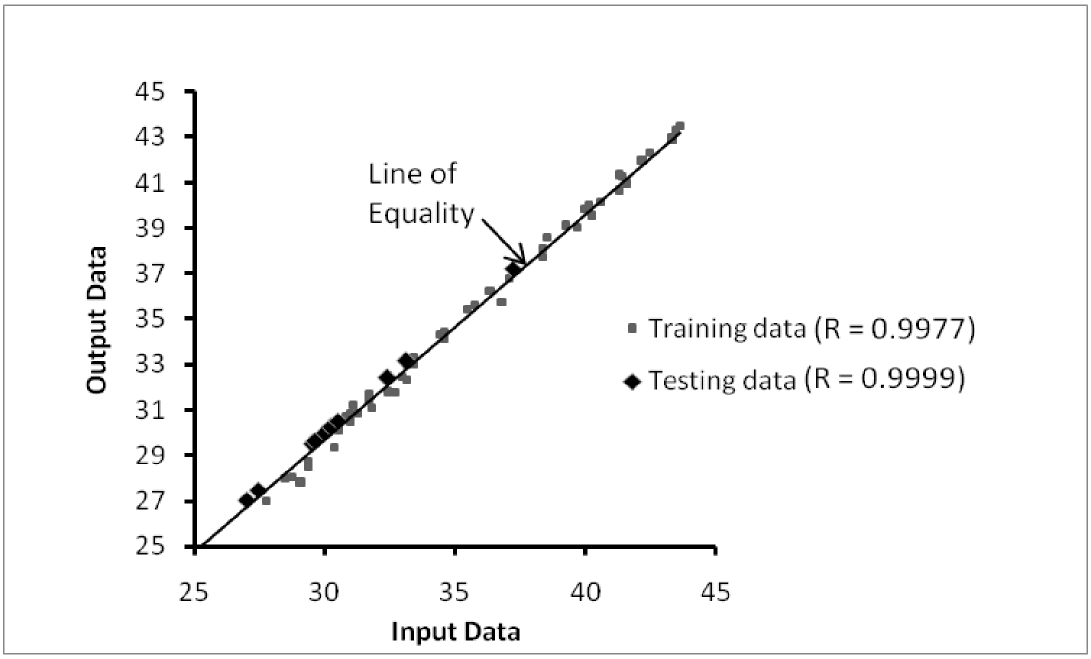
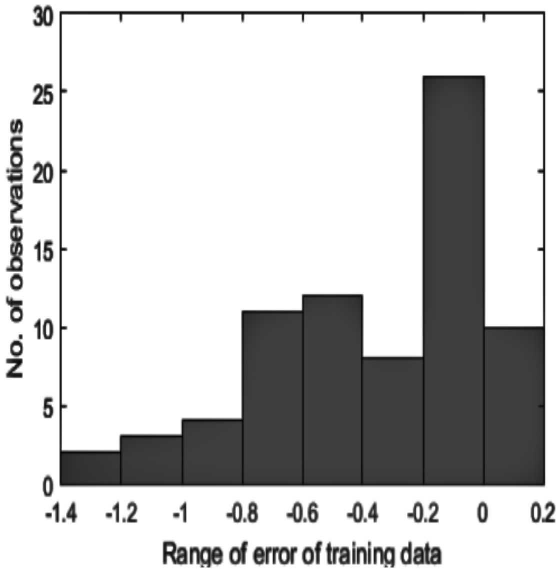


Figure 4 Comparison of predicted and observed compressive strength (MPa) of training and testing data



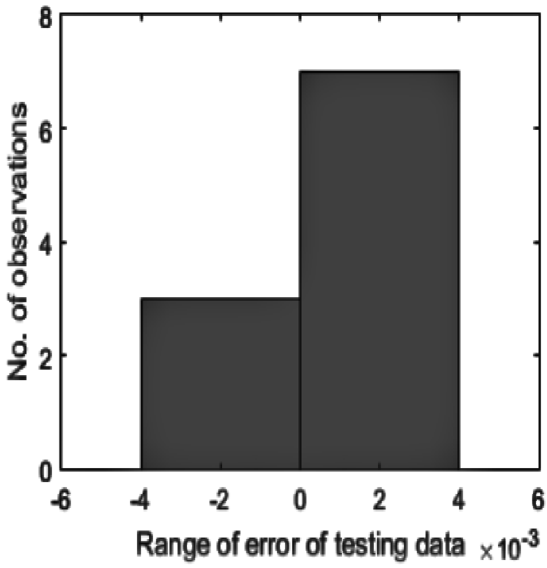


Figure 5 Error histogram of training dataset

Figure 6 Error histogram of testing dataset

Here, figure 4 represents the curve fitting of training and testing data which indicates how much the output values is closer to the given input values. The values which are closer to the line of equality give more accurate results.

Figures 5 & 6 represent the error histogram of training and testing data. It indicates the errors of given data lying between the different ranges. In training dataset (figure 5), the rang of error values is -1.4 to 0.2, and the error value of the maximum no. of observation is close to zero. Similarly, in testing dataset (figure 6) all the error values are lying between $-4*10^{-3}$ to $4*10^{-3}$ which are very small. Therefore, testing data gives more accurate results.

CONCLUSION

This work states the application of support vector machine for the estimation of average compressive strength of pumpable concrete based on its mix proportions. It is found that the maximum error of given training and testing data in the SVM model using Gaussian kernel is very small.

This study can be used to predict the compressive strength of pumpable concrete before its placement. A large number of variables are considered so that compressive strength can be predicted accurately but still there are variations in material, field conditions and curing conditions which have not been taken into account. In the future work these variations may be incorporated so that compressive strength can be estimated more precisely and accurately. In future we can also use other toolbox like K-nearest neighbours (KNN), Probabilistic Neural Network (PNN), etc. to model concrete strength.

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