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Prediction of Building Construction Project Cost Using Support Vector Machine

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ABSTRACT

Assessing construction costs with a more noteworthy level of accuracy during the early phase of construction is a basic element in building construction projects. This paper aims to develop a prediction model for building construction projects cost in India utilizing support vector machine (SVM) analysis. Complete 78 datasets of building construction projects were gathered from the Mumbai region of India for the development of the cost predictive model. The linear, Radial Basis Function (RBF), Polynomial, and sigmoid kernel function are applied for the development of the SVM model. The results of the developed Epsilon-SVR RBF kernel function-based SVM model show that better performance over the other models. The straight connection between actual construction cost and the predicted cost was likewise characterized by the coefficient of determination (R2), which was 94.29% along with the lowest error criteria. This research benefits the Indian construction industry by giving a general idea about the project cost prediction that will be useful to financial backers.

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1. Introduction

At the beginning phase of development, a piece of exceptionally restricted data about drawings and configuration is available so the enhancement cost assessment undertakes an essential part in the decision-making of the investors. Arrangement of a development quote for a construction project is a convoluted interaction since it includes the number of cost elements that ought to be effectively assessed dependent on appropriate analysis, past information, and knowledge. Because of the lack of information and data, the forecast of the development cost with a more significant level of accuracy comes to be an exceptionally important work for the cost estimator. The weak cost forecast may lead the project's prosperity into disappointment.

This research intends to construct and develop up a cost assessment model to foresee the construction cost of building structure projects at a beginning phase utilizing support vector machine analysis. Typically, the structural components, masonry work, finishing works, and so forth, have been a more noteworthy effect on the entire cost of building projects. In this investigation, 78 private construction project information was gathered from Mumbai and its close-by region, India. The support vector machine (SVM) technique has been employed to develop the cost forecast models. The proposed SVM model comprises a total of eleven design input variables, which can be effectively related to the assistance of engineering drawing and design information at the beginning phase while the construction cost plays the output of the model.

2. Literature review

The support vector machine (SVM) has various applications in different areas of civil engineering for forecast just as assessment reasoning. A portion of the basic works of SVM and other artificial intelligence techniques in construction cost prediction is referenced in this part.

Lin et al. introduced the PCA-PSO-SVM model, a support vector machine (SVM) model optimized by a particle swarm optimization (PSO) algorithm with principal component analysis, as a new hybrid substation project cost forecasting technique (PCA) [1]. A total of 65 datasets are used as input parameters into the PCA-PSO-SVM model for construction cost prediction. The MAPE and RMSE of the PCA-PSO-SVM model are 6.21 percent and 3.62 percent, respectively, indicating that the model has a higher forecast accuracy than other models and can be used to make substation investment decisions. M. Juszczyk developed several SVM-based regression models for estimating the cost of bridge construction projects. The root means square error (RMSE) and mean absolute percentage error (MAPE) of the constructed $BCCPM_{SVR}2$ model is about 1.111 and 10.94 percent, respectively, and the correlation coefficient (R) between real and expected cost is 0.980. Finally, the study found that the developed SVM model can provide accurate early forecasts of bridge construction costs [2]. For construction cost prediction, Cheng et al. developed an Evolutionary Support Vector Machine Inference (ESI) model using a genetic algorithm (fmGA) and a Support Vector Machine (SVM) approach [3]. M. Juszczyk presented a study of support vector regression models for the conceptual cost prediction for the residential building's projects [4]. Total of thirteen different input variables was utilized to develop three different SVM models. The results obtained from all three developed SVM models fulfill the error as well as regression criteria. Firas et al. developed two distinct SVM models to predict tunnel project time and cost indices. The SVM model 1 has a 13.9 % Mean Absolute Percentage Error (MAPE) and an average accuracy of 86.1 % (AA) while the second SVM model outperforms the first in terms of MAPE and AA forecasts, with 3.4 percent and 96.6 %, respectively [5]. S. Petruseva et al. developed a support vector machine (SVM) model to predict the bidding price utilizing datasets of fifty-four tenders from the various construction firms [6]. The developed SVM model has 2.5% of MAPE and 89.8% of prediction accuracy. The hybrid model is introduced by Petrusheva et al. to predict the construction cost of the road project. The SVM analysis and process-based time-cost model (TCM) were applied together to develop five different hybrid models. The SVM-Bromilow TCM model performs better than others with 97.61% accuracy and 1.01% MAPE [7]. Petruseva et al. overviewed the complete process of the Support vector machine and developed regression analysis models and support vector regression models to predict the project duration of construction projects. The developed SVM model with Radial Basis Function (RBF) kernel function has a coefficient of determination (R^2) 0.97405, and MAPE = 2.1722942 [8]. Finally, they concluded that the developed SVM model has better prediction along with greater accuracy over the linear regression model. Hong et al. performed a brief overview on various applications of Machine Learning techniques in the Building Life Cycle which was divided into nine important segments are Building Design, Construction, Cost analysis, Construction management, and documentation, Defect detection, building information modeling (BIM), Construction waste management, Building Operation and Maintenance, and Building control [9]. Yan K. and Shi C. developed an SVM model and ANN model to predict elastic modulus of normal and high strength concrete [10]. The results show that the developed ANN model has better predictions as compared to the SVM model.

Table 1 shows the summary of the comparative study of various artificial intelligence techniques applied for the prediction of construction project costs. The descriptive information regarding the various design input parameters which were utilized for the development Regression analysis as well as the various AI models like, Artificial Neural Network (ANN), Vector Machine (SVM), Decision Tree (DT), Principal Component Analysis (PCA), etc. also included. Most of the study was validated their developed models according to the regression criteria and performance was identified through error between actual cost versus predicted cost. The performance of the best model is also mentioned in Table 1 during this comparative literature study. Finally, the literature study concludes that the developed ANN and SVM models perform better than the statistical regression analysis model as well as the other AI models.

Table 1
The Summary for Comparative study of Artificial Intelligence Techniques in construction cost prediction

Sources;	Model	Area of Application	Input variables	Performance of Best Model
Salunkhe et al. [11]	Regression Analysis (RA) and Support Vector Machine (SVM)	Building construction costs prediction	Contracted price, contracted time, real price, real-time of construction, and the reasons for non-compliance of the deadline.	SVM Model: R^2=0.996 (99.6%), and MAPE = 0.30.
Cheng M. & Wu Y. [12]	Support Vector Machine (SVM), Neural Network (NN), & Evolutionary Fuzzy Neural Inference Model (EFNIM)	The construction conceptual cost estimation	Geology property, Earthquake impact, Decoration class, and Facility class.	NN Model: RMSE = 0.09
Qin et al. [13]	Principal Component Analysis (PCA) and Least Squares Support Vector Machine (LS-SVM)	The costs of a residential construction project forecasting	Construction area on the ground and below the ground, Building floors on the ground and below the ground, Layer high on the ground and below the ground, Base type, Structure type, Pile Type, Concrete price growth, Steel price growth, Seismic rating, Project management level, Earthwork processing difficulty, Facades.	LS-SVM Model: The relative error - 6.035%, & -1.297% Max. & Min. respectively.
Vahdani et al. [14]	Least Squares Support Vector Machine (LS-SVM), Regression Analysis (RA), & Back-Propagation Neural Networks (BPNNs)	Conceptual Cost Estimation in Construction Projects	Site area (in square meters), Geology property, Influencing householder number, Earthquake impact, Planning householder number, Total floor area (in square meters), Floor over ground (in stories), Floor underground (in stories), Decoration class, Facility class; and Normalized cost of the building project.	LS-SVM Model: R^2 = 0.8145 (81.45%), MSE = 0.1854, and MAPE = 0.30.
Kim et al. [15]	Regression Analysis (RA), Support Vector Machine (SVM), & Artificial Neural Network (ANN)	Estimation of school building projects cost.	Year, Budget, School Levels, Land Acquisition, Class Number, Building Area, Gross Floor Area, Storey, Basement Floor, and Floor Height.	ANN Model: Std. error = 0.92572 & MAER = 5.27
Meharie M. & Shaik N. [16]	Random forest (RF), Support Vector Machine (SVM), & Artificial Neural Network (ANN)	Prediction of the construction cost of projects at the early conceptual phase.	Project length, number of bridges, inflation rate, project scope, terrain type, project type, contract duration, and project location.	RF Model: Average RMSE = 0.9579
Son et al. [17]	Support vector regression (SVR) and Principal Component Analysis (PCA), Support vector regression (SVR), Artificial Neural Network (ANN), Decision Tree (DT), & Multiple Linear Regression (MLR)	A hybrid predictive model for cost performance of commercial building projects	Work type, Position, Experience, Project type (building use), Project duration, Project size.	PCA–SVR Model: MAE = 9.0305 RMSE = 11.6929 MAPE = 9.0196
Wang et al. [18]	Logistic Regression (LR), Single ANN_S, Bootstrap aggregating ANNs, Adaptive Boosting ANNs and Support vector machine (SVM)	Prediction of project cost and schedule success	The total project cost range, total schedule range, average PDRI score.	Adaptive Boosting ANNs and Support vector machine (SVM) Model: Overall Prediction accuracy 80.0% & 76.0% resp.

3. Support vector machine

The support vector machines technique was developed by Vapnik (1995), part of a machine learning approach follows the theory of reduction of fundamental probability and numerical understanding. SVMs can categorize model statistics applying linear models using nonlinear plotting into a high-level element room. SVMs, like neural networks, require data instances to be trained and tested. The SVMs algorithm aims to reduce the generalization error's upper bound. This allows the SVMs to oversimplify even after dispensing with data that has not been seen before. SVMs have many advantages over ANNs, including effective use of large element room, a distinctively fathomable optimization challenge, and the capability to be hypothetically assessed applying algorithmic understanding hypothesis. SVMs have recently been used effectively in construction industry problems for example building construction cost estimation [4,12–15], highway construction [7,16], and concrete strength prediction [10]. The theoretical background of the SVM model is summarized below.

SVM methods can be used to solve regression problems, i.e., functional approximation problems. The machine learning is offered l training data from which it tries to understand the input-output connection (reliance, representation, or function) $f(x)$ in the specific regression training challenge. In SVM analysis, a training data set D = $\{[\,\boldsymbol{x}(i), y(i)] \in R^n \times R, i = 1, \ldots, l\}$ contains of l sets $(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), \ldots, (\mathbf{x}_l, y_l)$, where the responses $\mathbf{x}$ are n-dimensional vectors $\mathbf{x} \in R^n$ and method responses $y \in R$, are continuous values.

The SVM's regression together with a linear regression hyperplane $f(x, w)$ presented as

$$f(x, w) = w^T x + b \tag{1}$$

Rather than the margin used in classification, in SVM regression, the measurement of error approximation is carried out. The most distinct change from traditional regression is that employs fictional loss (error) mechanisms.

The linear error function of Vapnik, with the ε-insensitivity region, is described as.

$$E(\mathbf{x}, y, f) = |\, y - f(\mathbf{x}, \mathbf{w}) \,|_\varepsilon = \begin{cases} 0 & \text{if, } |\, y - f(\mathbf{x}, \mathbf{w}) \,| \le \varepsilon, \\ |\, y - f(\mathbf{x}, \mathbf{w}) \,| - \varepsilon, & \text{else} \end{cases} \tag{2}$$

or as,

$$e(\mathbf{x}, y, f) = \max(0, |y - f(\mathbf{x}, \mathbf{w})| - \varepsilon) \text{ [19].} \tag{3}$$

If the variation amongst the expected $f(xi, w)$ and the computed amount yi is less than, the deficit is equal to 0. The ε-insensitivity loss function of Vapnik describes an ε tube. The deviation (error or cost) is zero if the expected quantity is underneath the tube. The deficit is proportional to the application of the variation amongst the forecasted amount and the tube radius ε for each additional measured things beyond the tube.

4. Methodology

This study aims to build up a model to foresee the construction cost of building projects at the beginning phase of construction using the Support Vector Machine technique. The procedure embraced for this investigation is apportioned into three significant sections. The initial segment related to the identifying the Key influencing factors over the construction cost during the beginning phase. The subsequent part concerns the development of different SVM models utilizing different SVM kernel functions. The third part concerns the comparative study for the developed cost prediction models based on the results for assessing the construction cost. Figure 1 addresses the applied approach of this research.

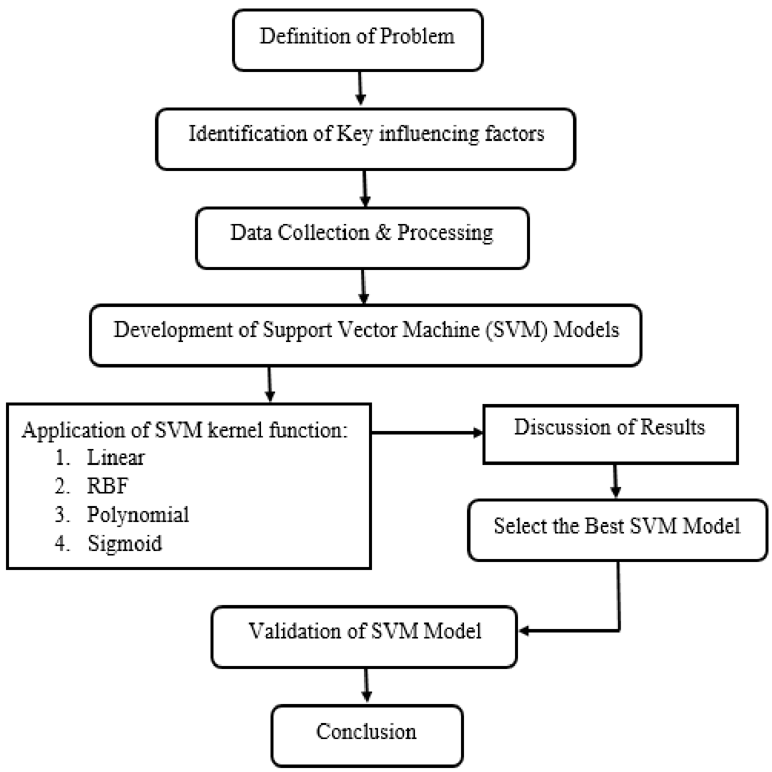

Fig. 1. Flow chart for the methodology adopted.

4.1. Identification of key influencing factors

According to the Indian construction industry, identification and selection of building construction cost Key influencing factors is a critical process to develop SVM model. The literature survey of this study endeavors to distinguish the exceptionally massive cost factors from the previous related study. Also, the suggestions from the structural designing professionals, building contracting firms, and architectural firms of the Indian development industry. Total 11-key expense huge autonomous factors of the structure development projects were recognized to assess the development cost of building projects at the beginning phase. Table 1 shows the description of all eleven Key influencing factors (Predictor) and construction cost (Target) for the development of SVM cost prediction models.

Table 2
SVM Model prediction's influencing factors.

Symbol	Variables	Code	Type	Type
x_1	Ground Floor Area	m^2	Continuous	Predictor
x_2	Typical Floor Area	m^2	Continuous	
x_3	No. of Floors	Nos.	Continuous	
x_4	Structural Parking Area	m^2	Continuous	
x_5	Quantity of Elevator Wall	m^3	Continuous	
x_6	Quantity of Exterior Wall	m^3	Continuous	
x_7	Quantity of Exterior Plaster	m^2	Continuous	
x_8	Area of Flooring	m^2	Continuous	
x_9	No. of Columns	Nos.	Continuous	
x_{10}	Type of foundation	➢ Isolated footing = 1 ➢ Isolated and combined footing = 2 ➢ Raft foundation = 3	Categorical	
x_{11}	No. of Householders	Nos.	Continuous	
y	Construction Cost	Indian Rupees Rs. /-	Continuous	Target

4.2. Data collection and processing

In this research, the SVM model is utilized to forecast the construction cost of building construction projects in India. Total 78 sample datasets consist of the cost data of eleven crucial parameters, which were completed in recent years (2018-2020). The data set and imperative basic records were gathered from the different gatherings engaged with the construction business-like; the structural designing professionals, building contracting firms, architectural firms, and real estate developers, which are in Mumbai and its close by districts, India. The excel spreadsheet is developed for the normalization of the database to avoid overfitting during the training of the SVM model. The formula used for normalizing the training data sets to fall in the interval [-1, 1] is given by equation 4.

$$P_i^{norm} = \left[2\left(\frac{P_{i\,-}\;P^{min}}{P^{max}-\;P^{min}}\right)\right] - 1 \tag{4}$$

4.3. Development of SVM model

In this research, the software package DTREG is utilized to develop a predictive Support Vector Machine model. DTREG provides numerous categories of SVM models, for classification and regression operations, also it delivers an easy-to-understand interface.

DTREG provides a total of four various kernel functions, including sigmoid, radial basis function (RBF), polynomial, and linear functions, which are suitable for various types of datasets to be utilized. In this research, the Epsilon- Support Vector Regression (SVR) models were developed by using all available kernel functions to determine the best model. The Epsilon value (ε), that is a tolerance function whose significance is also modified to regulates the stopping criteria of the optimization procedure of the SVM technique. To increase the accuracy of the model it can be reduced, and the computation time can be minimized if it is increased. The research included a total of five different SVM-centered regression models. A Network architecture of the developed SVM model is shown in Figure 2.

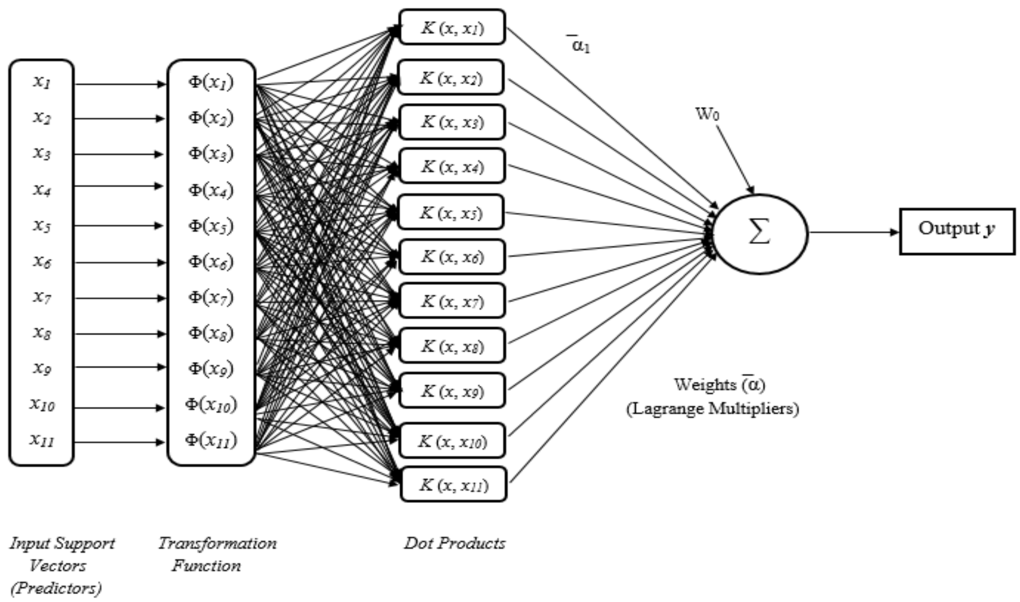

Fig. 2. Network architecture of the SVM model.

5. Results and discussion

The development and reliability of the SVM regression model in the DTREG software can be validated utilizing three different methods. In the first method (random percent validation), an arbitrary part of rows from the input data set is identified and applied during the validation phase once the training process is completed. In the second method, the number of rows from the input data set is selected for the validation process. The third method (10-fold cross-validation) where a V-1/V percentage of the rows after the input information record is utilized during the training phase of every SVM regression model while the remaining information records are applied for the validation process. In this research the third method, 10-fold cross-validation is adopted to construct, train, and validate the SVM regression model for the prediction of construction cost.

The summary descriptive statistics of the developed SVM models during the training phase is shown in Table 3. During the training as well as the validation phase of all SVM models, the RBF kernel function-based Epsilon-SVR model performs better than the other developed model.

The statistical description of all developed SVM models during the validation phase is summarized in Table 4. The precision of the established model is determined by employing regression criteria includes the coefficient of determination (R^2) and coefficient of correlation (R) amongst the actual cost and predicted cost. Also, the error criteria; Root Mean Squared Error (RMSE), Mean Squared Error (MSE) and Mean Absolute Percentage Error (MAPE) are considered to investigate the performance of the model.

Table 3
Statistics for training data of the SVM models.

Sr. No.	Description	SVM Model Linear kernel Function	SVM Model RBF kernel Function	SVM Model Polynomial kernel Function	SVM Model Sigmoid kernel Function
1	Mean target value for input data	-0.7651538	-0.7651538	-0.7651538	-0.7651538
2	Mean target value for predicted values	-0.7782058	-0.7689507	-0.7694709	-0.7782138
3	Variance in input data	0.0777043	0.0777043	0.0777043	0.0777043
4	Residual (unexplained) variance after model fit	0.0090458	0.0005231	0.0004757	0.0091298
5	Proportion of variance explained by model (R^2)	0.88359	0.99327	0.99388	0.88251
6	Coefficient of variation (CV)	-0.124301	-0.029891	-0.028504	-0.124877
7	Normalized mean square error (NMSE)	0.116413	0.006732	0.006122	0.117494
8	Correlation between actual and predicted (R)	0.956814	0.996722	0.997056	0.955953
9	Maximum error	0.7387479	0.1706477	0.1617297	0.7409057
10	RMSE (Root Mean Squared Error)	0.0951095	0.0228715	0.0218099	0.09555
11	MSE (Mean Squared Error)	0.0090458	0.0005231	0.0004757	0.0091298
12	MAE (Mean Absolute Error)	0.0333417	0.0085171	0.0084572	0.0338902
13	MAPE (Mean Absolute Percentage Error)	5.4303524	1.2179244	1.2075008	5.5121312

Table 4
Statistics for Validation data of the SVM models.

Sr. No.	Description	SVM Model Linear kernel Function	SVM Model RBF kernel Function	SVM Model Polynomial kernel Function	SVM Model Sigmoid kernel Function
1	Mean target value for input data	-0.7651538	-0.7651538	-0.7651538	-0.7651538
2	Mean target value for predicted values	-0.7794639	-0.7637906	-0.75997	-0.7796589
3	Variance in input data	0.0777043	0.0777043	0.0777043	0.0777043
4	Residual (unexplained) variance after model fit	0.0101779	0.0044302	0.0083103	0.01026
5	Proportion of variance explained by model (R^2)	0.86902	0.94299	0.89305	0.86796
6	Coefficient of variation (CV)	-0.131850	-0.086989	-0.119140	-0.132381
7	Normalized mean square error (NMSE)	0.130982	0.057014	0.106948	0.132040
8	Correlation between actual and predicted (R)	0.951485	0.975257	0.969106	0.951567
9	Maximum error	0.7800992	0.3387325	0.5546376	0.7822388
10	RMSE (Root Mean Squared Error)	0.1008855	0.0665597	0.0911608	0.1012919
11	MSE (Mean Squared Error)	0.0101779	0.0044302	0.0083103	0.01026
12	MAE (Mean Absolute Error)	0.0371639	0.0372062	0.043735	0.0376084
13	MAPE (Mean Absolute Percentage Error)	6.4338369	8.9694542	8.5633603	6.7339685

The Epsilon-SVR RBF kernel function-based model having the (R) = 0.975257 which indicates the better correlation amongst the actual and predicted cost and the overall accuracy of the model, (R^2) = 0.94299 i.e., 94.29%. The MAPE generally indicates the accuracy of the model in the percentage form. MAPE = 8.96 indicates that the Epsilon-SVR RBF kernel function-based SVM model's percentage error is 8.96 % in this case. The other error criteria RMSE = 0.0665 and MSE = 0.0044 are also close to zero which is considered as an excellent predictive result. Figure 3 shows the validation of the SVM model along with the correlation of the actual construction cost versus the predicted cost.

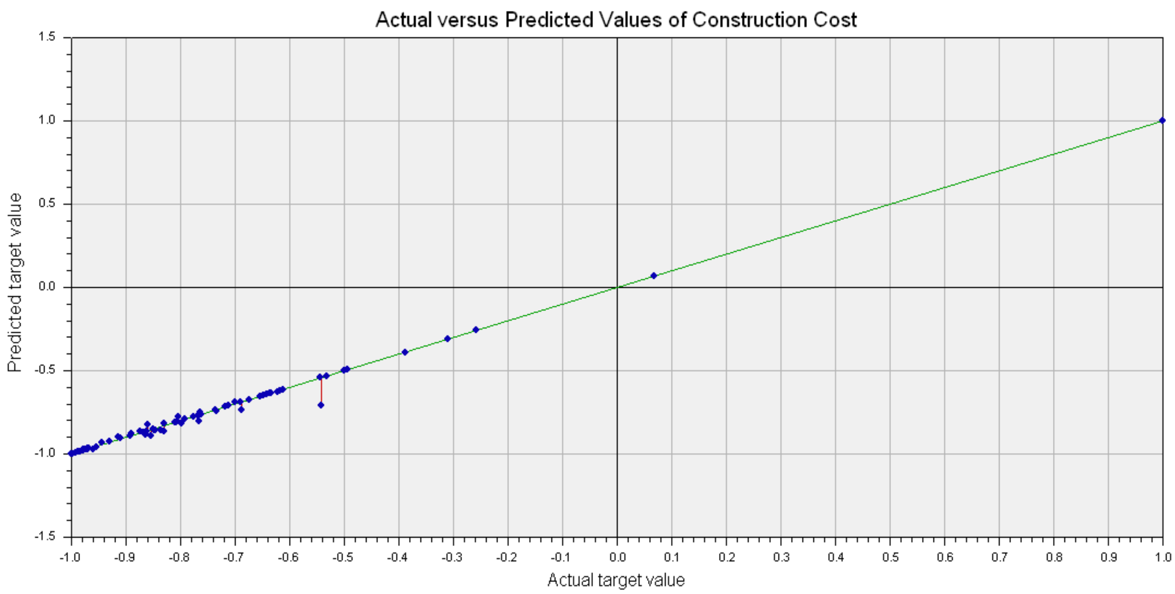

Fig. 3. Validation of SVM Model.

The sensitivity analysis is performed to identify the relative significance of the interpreters for the SVM model shown in Table 5.

Table 5
Overall Importance of Variables.

Variable	Importance
Typical Floor Area	100.000
Quantity of Exterior Wall	54.109
Area of Flooring	41.837
Structural Parking Area	40.393
Ground Floor Area	36.617
No. of Floors	32.481
Quantity of Exterior Plaster	24.991
No. of Householders	13.982
Quantity of Elevator Wall	3.890
Type of Foundation	2.734
No. of Columns	1.962

6. Conclusion

Since cost estimation is one of the most crucial aspects of effective construction management and the success of the project, this research aimed to develop a cost prediction model that could accurately forecast project costs even early in the project's life cycle. This research investigates the development of a cost estimation model using 78 datasets from building structures projects to construct a data-driven SVM model.

The 10-fold cross-validation method was selected to develop four different SVM models for the prediction of construction cost. The linear, Radial Basis Function (RBF), Polynomial, and sigmoid kernel function were utilized to construct, train and validate the SVM model. The developed Epsilon-SVR RBF kernel function-based SVM model had a correlation coefficient (R) = 0.975257 and (R2) = 0.94299 between the actual and predicted cost defines the overall accuracy as a 94.29%. The MAPE shows the model's percentage error as 8.96 % which satisfies the error criteria.

Such cost prediction models offer an overall thought regarding the spending plan of the venture consequently better choices can be made. This investigation plays a significant part in finance as well as construction management. Likewise, it is being able to see huge and complex information rapidly with modern factual strategies that improve the precision and nature of dynamic. At long last, this study contributes to the Indian construction industry and conveys a practical idea about cost forecasting which will be useful to the financial backers.

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