Case Study

Support vector machine for determining the compressive strength of brick-mortar masonry using NDT data fusion (case study: Kharagpur, India)

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Abstract
The accurate prediction of compressive strength of brick-mortar masonry walls is crucial for the damage assessment of load-bearing masonry constructions. Direct tests conducted to estimate compressive strength involve core drilling and are expensive. To estimate compressive strength, several indirect test parameters can be used as empirical predictors. Nondestructive tests can be rapidly executed, can significantly reduce repair costs, and can increase the knowledge level of buildings by indirectly estimating compressive strength. This study aimed to determine the compressive strength of masonry construction by using support vector machines (SVMs). Input variables of the model are test data obtained from the nondestructive and destructive testing of 44 masonry wallettes cast in a laboratory for evaluating the compressive strength of brick (f_b), rebound hammer number, and ultrasonic pulse velocity, while the compressive strength of the wall (f_c) is output. The final results obtained using an SVM model are validated for a masonry building in Kharagpur, India through experimental testing, and these results are compared with other established empirical relationships. The results indicate that the SVM can be efficiently used to predict the compressive strength of brick-mortar masonry.

Keywords Machine learning · Intelligent algorithms · Nondestructive testing · Structural health monitoring

1 Introduction

An increase in the global population resulted in the construction of new structures to accommodate the continually increasing populace. People are living in old masonry buildings, which must be evaluated for their remaining service life by monitoring and using test strategies. A typical masonry building has load-bearing walls made using brick-mortar units, which supports a complete superstructure. This typology of buildings were widely constructed in India until the mid-1900s for building smaller residential structures. Apart from residential structures, this topology is commonly used for the construction of domes, roofs, and chimneys. If the conservative estimate of the remaining life of buildings is known, the buildings can be repaired before time. On the other hand, inaccurate estimation of the service life may cause severe damages, which results in the loss of life, rehabilitation, and major repairs, thus increasing the cost. Therefore, an accurate prediction of the service life is necessary to avoid such extreme circumstances and minimise damage progression in terms of repair costs.

Among various health monitoring indicators of masonry buildings, compressive strength is considered most crucial. Masonry buildings are subjected to compressive loads throughout their service life [1, 2], thus assessing

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their behaviour in compression is crucial. Although compressive strength can be estimated by extracting core samples from the building, this approach is not preferred because tests are costly and intrusive. Therefore, the prediction of the compressive strength of the masonry structures joined using mortar without causing damage is a global concern to safeguard buildings and prolong their use. With time, the compressive strength of brick walls of buildings decreases because of factors, such as ageing and material degradation caused by weathering. Therefore, empirical relations developed using various experimental studies [3–11] and design codes [12, 13] inaccurately estimate compressive strength. Moreover, the empirical relations are site-specific and based on old data for their calibration, and the training data must be updated with the new test data obtained from sites. The compressive strength of masonry depends on the strength of individual components (brick and mortar) and construction processes, which deteriorate estimation capacity. Various destructive and nondestructive methods are available that can be used to estimate the strength of the building.

Damage assessment in masonry structures for service life prediction is performed using multiple nondestructive techniques. The NDT data collected using various techniques and sensors are heterogeneous and are crucial for structural health monitoring. McCann and Forde [14] in their review paper summarised several ND techniques used for masonry constructions. Several researchers have developed empirical correlations between compressive strength with data from NDTs. Several studies have used regression analyses to obtain the correlations between compressive strength and mechanical parameters to quantify the strength of buildings. For example, Ramos et al. [15] fused ultrasonic, sonic, and direct core tests to determine the elastic modulus of masonry materials used in a church, which is an indicator for material degradation. Mishra et al. [16] used natural frequencies obtained through experimental modal analysis as a NDT technique to capture the extent and location of damages on the cantilever beam. Moreover, other ND techniques, such as rebound hammer (RH) [17], ultrasonic pulse velocity (UPV) [18], flat-jack method [19], impact-echo method [20], ground-penetrating radar [21], ferroscan testing [22], infrared thermography [23], and laser scanning [24], are commonly employed by various researchers. The integration of diverse sources of data to predict structural damages is a challenging task. This study integrates various ND techniques to estimate the compressive strength of brick-mortar masonry. The integration of various ND techniques reduces uncertainty in the estimation of required parameters [25–27].

Numerous novel artificial intelligence techniques have been used for various engineering applications. Advancement in soft computing techniques has enabled the effective use of data and clear interpretation by engineers. The SVM has been used to solve various problems involving predicting the compressive strength of different types of concrete [28–31] and jet-grouted material [32]. Apart from estimating compressive strength, the SVM is used for several applications in engineering, such as traffic sign detection [33], modelling soil pollution [34], predicting daily flow of river [35] predicting elastic modulus of concrete [36], modelling landslide susceptibility [37], air balancing for ventilation systems [38] and predicting shear force for base isolation device [39, 40]. Its other successful applications include for example, classifying building information modelling elements [41], system reliability analysis of slopes [42], estimation of concrete expansion caused by alkali-aggregate reaction [43], damage detection in a three-story frame structure [44], prediction of lateral load capacity of piles [45], crack inspection for aircraft skin [46] and assessing liquefaction potential [47].

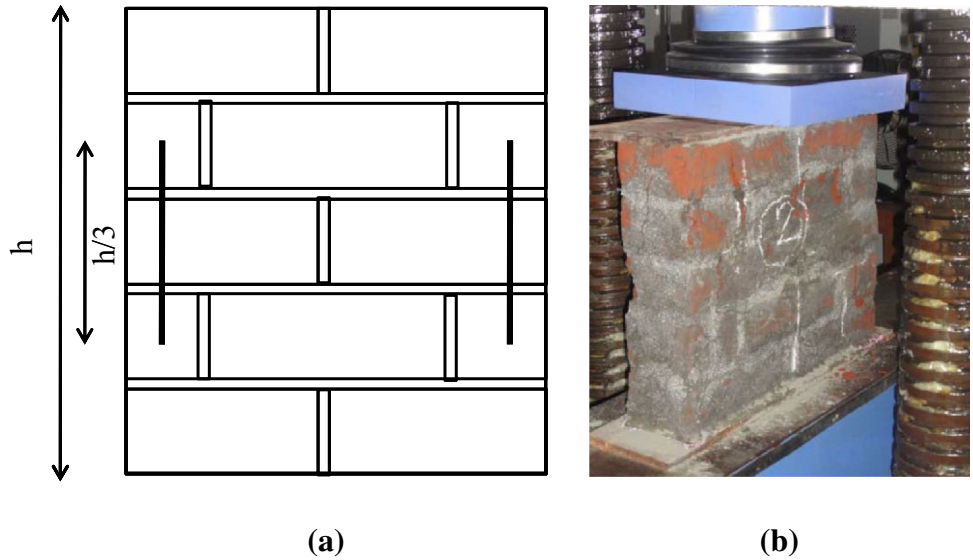
In this study, the SVM is used as a data intelligent model to predict the compressive strength of brick-mortar masonry walls based on nondestructive evaluation. The paper is organised as follows: Sect. 1 introduces the aim of the paper and several application of SVM method in civil engineering field. Section 2 describes the procedure involved to collect experimental data from the laboratory testing of masonry wallets. Section 3 presents the SVM model applied for NDT data fusion. Section 4 describes the building tested for the case study. Section 5 presents the results of the proposed SVM methodology and its comparison with existing empirical models. Finally, in Sect. 6 conclusions and discussions of future works are presented.

2 Data collection

To develop the data intelligent model, experiments are performed in the structural laboratory at Kharagpur to gather data from 44 masonry wallettes for evaluating their performance in compression [48]. The wallettes are classified into three groups (I, II, and III) based on the strength of bricks used for casting. Figure 1a and b presents the test setup with five courses. Before conducting direct compression tests, two NDTs, namely RH and UPV tests, are performed. The obtained experimental results have the ultimate compressive strength and failure load. Figure 2 reports the readings of all data obtained from the experimental testing of masonry wallets.

Table 1 reports the statistical data obtained with their range, mean, and standard deviations. Furthermore, the mechanical properties of individual units, namely bricks and mortars, are obtained through compressive tests. According to IS 1077:1992 [49] code for wall bricks, the

Fig. 1 **a** A typical masonry wallette and **b** masonry wallette subjected to compressive testing machine



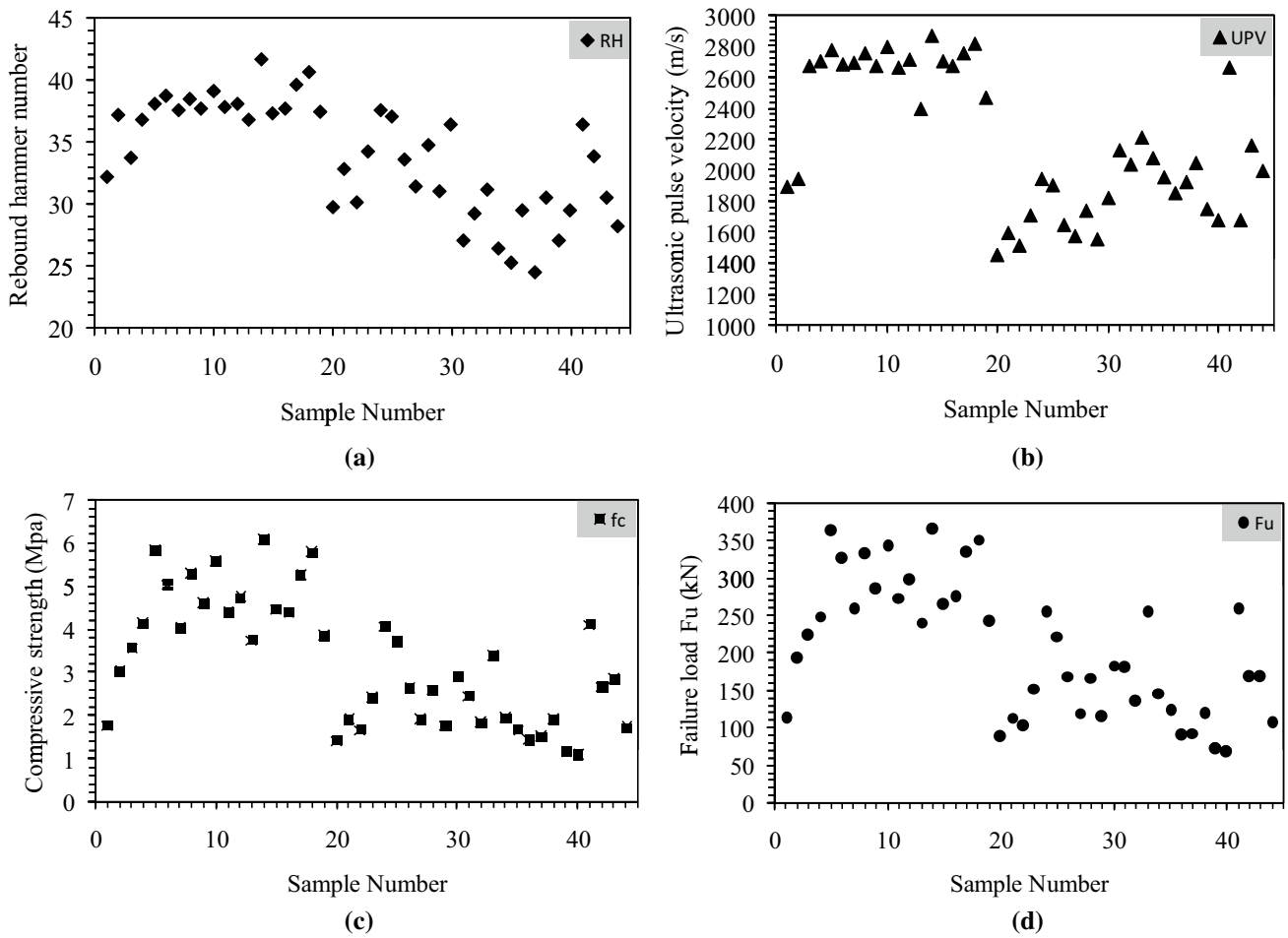


Fig. 2 Dataset generated through experimental testing for service life indicators: **a** RH, **b** UPV, **c** f_c, **d** F_u

Table 1 Boundary range of the input and output variables

Parameter	Category	Min.	Max.	Mean	SD
Rebound number RH	Input	24.60	41.70	34.01	4.51
Ultrasonic pulse velocity UPV (m/s)	Input	1458	2870	2191	461
Compressive strength of brick f_b (kN)	Input	10.15	20.60	15.45	4.80
Compressive strength f_c (MPa)	Output	1.09	6.07	3.24	1.46
Failure load F_u (kN)	Output	68.05	365.27	205.05	89.20

compressive strength of type I, II, and III bricks are 20.6, 10.15, and 12.2 MPa, respectively. Moreover, cubes of mortar units comprising one part of cement and four parts of sand are cast based on the standards of IS 2116: 1980 [50]. Compression tests are performed under the same condition. The average value of compressive strength for mortar cubes is 14.3 MPa.

3 Support vector machine

Support vector machine (SVM), which was developed by Cortes and Vapnik [51] in the early 1990s. SVM is used for prediction purposes and is an effective pattern recognition tool. The method is suitable for cases with small sample size. SVM can overcome the limitations of artificial neural networks with regard to bad generalisation capabilities. SVM regression, which is referred to as support vector regression (SVR) [52], is a powerful method for solving regression problems by using the alternative loss function. SVR modifies the low-dimensional original input data (x) into high-dimensional output data through nonlinear transformation. The transformation allows the identification of nonlinear separating features that cannot be recognised in a low-dimensional space. The SVR method involves structural risk minimisation rather than the minimisation of the mean square error over the data set. SVM is used in this study to predict the compressive strength of brick-mortar masonry, which is modelled as a regression problem. The mathematical formulation of SVR is as follows.

Consider a training dataset with D dimensions (number of NDT test data in this study) denoted by $x_1, y_1),..., (x_i, y_i),.. (x_N, y_N)$, $i = 1,...,N$, where x_i is the D-dimensional input vector and y_i is the scalar output or target value for N number of datasets. In this study, f_b, RH, and UPV are used as the input parameters ($x = f_b$, RH, UPV) to determine the best-fit function $f(x)$. The nonlinear relationship between the input and target values can be formulated using the regression function as follows:

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

where $f(x)$ and $\phi(x)$ denote the forecasting values and nonlinear mapping function in high-dimensional space; w denotes the matrix representing the orientation of hyperplane separating the datasets, and b represents the bias coefficient to be adjusted. These coefficients are computed by minimising the regularised risk function.

$$R(C) = \frac{1}{2}||w||^2 + R_{emp} = \frac{1}{2}||w||^2 + C\frac{1}{N}\sum_{i=1}^{N}(L_\varepsilon(y_i, f(x_i)) \tag{2}$$

where $L_\varepsilon(y_i, f(x_i))$ is the Vapnik's ε-insensitive loss function, which is formulated as follows [53]:

$$L_\varepsilon(y_i, f(x_i)) = \begin{cases} 0 & if\ |y_i - f(x_i)| - \varepsilon \le 0 \\ |y_i - f(x_i)| - \varepsilon & otherwise \end{cases} \tag{3}$$

where $R(C)$ and R_{emp} denote the regression and empirical risks, respectively. The first term in Eq. (2) is the regularisation term, and the second term in Eq. (2) is estimated from the ε-insensitive loss function in Eq. (3). The constant C ($0 < C < \infty$) denotes the trade-off between the maximisation of the margin (Fig. 3a) and the training error. The parameter ε denotes the insensitive loss function for the radius around the training data (Fig. 3b).

Two positive slack variables (ξ and ξ^*) can overcome the noise in the data. These variables are denote the distance between the actual values and analogous boundaries of the ε-tube (Fig. 3a, b). Equation (2) can be formulated into the following equation:

$$Minimise\ R(w, \xi, \xi^*) = \frac{1}{2}||w||^2 + C\sum_{i=1}^{N}(\xi + \xi^*) \tag{4}$$

$$subjected\ to = \begin{cases} y_i - w\phi(x_i) - b \le \varepsilon + \xi_i \\ -y_i + w\phi(x_i) + b \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \ge 0 \end{cases} \tag{5}$$

The problem, which is now presented as an optimisation problem, can then be converted into a dual formulation by a Lagrange multiplier as follows:

$$Maximise\ R(\alpha_i, \alpha_i^*) = -\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}(\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*)K(x_i, x_j) - \varepsilon\sum_{i=1}^{N}(\alpha_i + \alpha_i^*) + \sum_{i=1}^{N} y_i(\alpha_i - \alpha_i^*) \tag{6}$$

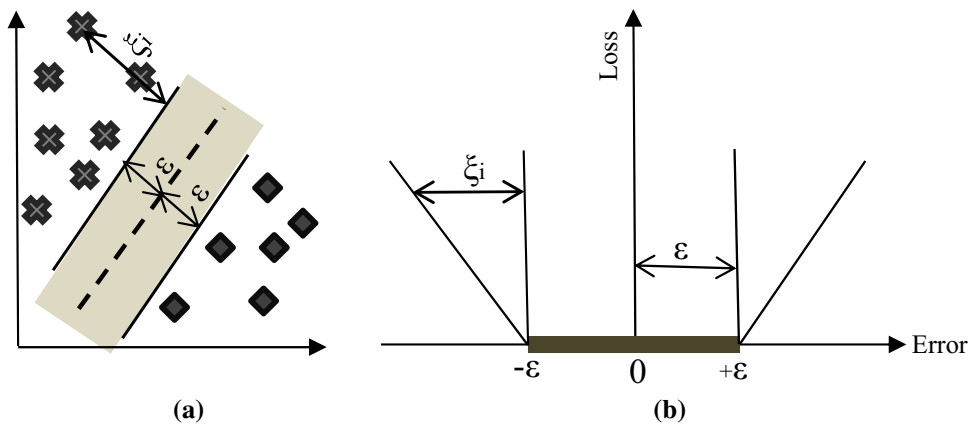


Fig. 3 **a** Example of a linear SVR, **b** ε-insensitive loss function

$$subject\ to \sum_{i=1}^{N}(\alpha_i - \alpha_i^*) = 0;\ 0 \le \alpha_i, \alpha_i^* \le C \tag{7}$$

where α_i, α_i^*, and $K(x_i, x_j) = \phi(x_i)^T\phi(x_j)$ denote the Lagrange multipliers. The Gaussian kernel function is defined using the following formula:

$$K(x_i, x_j) = exp(-\gamma||x_i - x_j||^2) \tag{8}$$

where γ is the kernel parameter. The coefficient w (Eq. 1) can be computed from the Lagrange multiplier by using the following equation:

$$w = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)\phi(x_i) \tag{9}$$

Finally, the prediction function of nonlinear SVR is formulated as follows:

$$f(x) = \sum_{i=1}^{N}(\alpha_i - \alpha_i^*)K(x_i, x) + b \tag{10}$$

In this study, the training (44 datasets obtained from the laboratory testing of masonry wallettes) and testing (a case study of building diagnosis having five datasets) of SVM for the regression problem is performed using MATLAB [54]. The trial and error is done for tuning SVM parameters (C, γ, ε) by comparing the accuracy of predicted and actual values of compressive strength of brick-mortar masonry. The values of SVM parameters are found out to be 500, 250 and 0.001 for C, γ, ε respectively. The tuning parameters of the SVM model can also be optimised by utilising metaheuristic optimisation algorithms which minimise the objective function in terms of mean square error formulated as the difference between predicted and actual values. Yu et al. [40] optimised SVR parameters using fruit fly optimisation algorithm to characterise an elastomer base isolator for controlling structural vibrations. In another study, SVM-based model parameters were optimised by particle swarm optimisation algorithm to predict the concrete expansion due to alkali-aggregate reactivity [43].

The flowchart at Fig. 4 succinctly explains the procedure to determine the residual compressive strength of masonry wall by combining the ultrasonic pulse velocity and rebound index readings. The last step of data fusion is done by using a trained SVM model developed over the experimental data captured from the laboratory testing of masonry wallets. Once the compressive strength is estimated, the engineer can then make the decision to adopt a particular retrofitting technique to strengthen the structure.

4 Case study (Kharagpur, India)

In this case study, masonry samples are collected in the form of old bricks and masonry blocks from one of the demolished building sites at Kharagpur, India (Fig. 5a). The building was constructed in 1962 by using brick-mortar masonry as the primary load-bearing system. In this study, 15 masonry bricks and 7 blocks of load-bearing walls are retrieved from the demolished building site. As discussed in Sect. 2, IS codal guidelines are followed for the preliminary study of the masonry constituents in terms of masonry units and mortar. The specimens are tested using NDT parameters for obtaining values of RH and UPV (Fig. 6a–c). Table 2 shows the dimensions and parameters obtained using both NDTs and direct compressive tests for 8 specimens. The estimation of the mortar compressive strength of the old structure is based on the provisions of IS: 2250 - 1981 [55] code of practice for preparing and using masonry mortars. Certain generalisations are made for strength assessment. To simulate the conditions and incorporate the effect of age, the mortar constituents

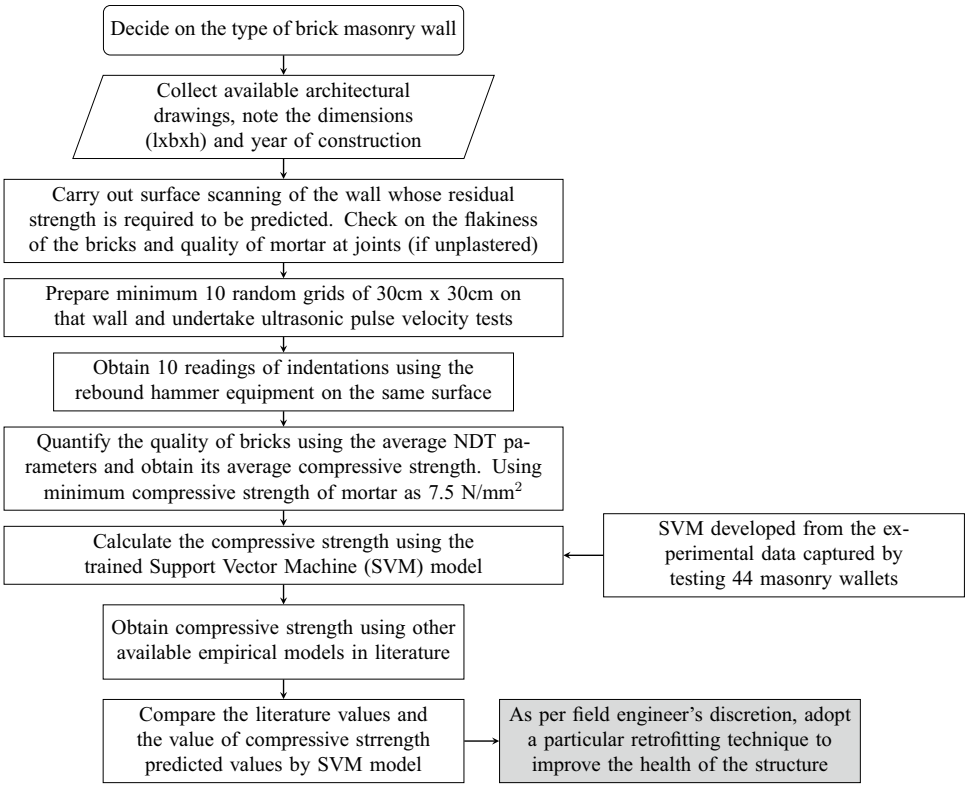


Fig. 4 Flowchart summarising the procedure for determining residual compressive strength of brick masonry

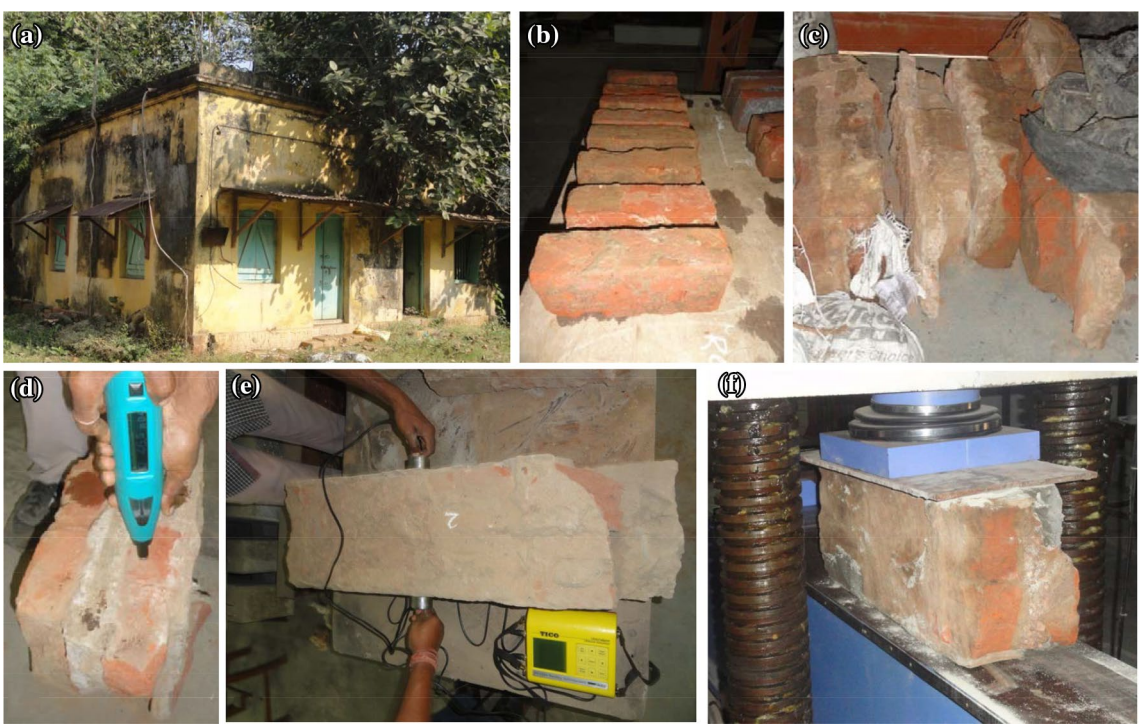


Fig. 5 **a** The building tested at Kharagpur, India, **b** and **c** masonry units and blocks obtained from the demolished building, **d** RH on masonry blocks, **e** UPV on masonry blocks, and **f** smoothened masonry blocks tested for compressive strength

Fig. 6 **a**–**c** NDT on masonry constituents and **d** and **e** destructive tests for brick and mortar

Table 2 Experimental readings for old building brick specimens

Specimen nos.	Dimensions (in cm) L × B	RH	UPV (m/s)	Failure load (kN)	Compressive strength (N/mm^2)
B-1	25.2 × 12.7	33.8	940	382.13	11.94
B-2	25.0 × 11.6	38	1280	279.27	9.63
B-3	25.5 × 12.7	31.8	1190	340.04	10.5
B-4	25.3 × 12.8	34.7	1260	268.79	8.3
B-5	24.5 × 12.7	33.65	1160	289.06	9.29
B-6	26.0 × 13.0	30.7	790	275.81	8.16
B-7	25.0 × 11.9	41.65	1620	366.82	12.33
B-8	25.0 × 12.8	32.65	1360	320.96	10.03
Average		34.65	1200	315.36	10.02
SD		3.58	253	43.87	1.53

Table 3 Experimental readings for old building mortar specimens

Specimen nos.	Dimensions (in cm) L × B	RH	UPV (m/s)	Failure load (kN)	Compressive strength (N/mm^2)
M-1	15.0 × 15.0	15.1	3020	145.64	6.47
M-2	15.1 × 15.0	15.7	2950	138.78	6.16
M-3	14.9 × 15.1	16.15	3020	146.59	6.51
M-4	15.0 × 15.1	15.9	2990	156.52	6.95
M-5	15.0 × 15.0	15.55	3020	157.01	6.97
Average		15.68	3000	148.89	6.61
SD		0.39	31	7.79	0.35

Table 4 NDT readings obtained from masonry blocks extracted from the old building

Specimen nos.	Dimensions (in cm) L × B × H	RH	UPV (m/s)
MB-1	57.5 × 26.5 × 20.5	31.9	2065
MB-2	80.5 × 28.0 × 21.5	33.7	2112
MB-3	59.5 × 26.0 × 18.6	34.4	2215
MB-4	65.0 × 26.5 × 19.0	36.7	2315
MB-5	43.5 × 23.2 × 18.8	25.7	1773
Average		32.5	2096
SD		4.2	205

of the specimen are assumed to be 1:6 for low-strength cement of Ordinary Portland Cement (OPC) grade 33. Such mortar cubes are evaluated for its compressive strength (Fig. 6d). Table 3 reports the dimensions, NDT parameters, and compressive strength of mortar cube specimen. The compressive strength of old bricks is then evaluated based on IS 1905:1992 [49] (Fig. 6e).

The masonry blocks (Fig. 5b–c) are obtained from one of the load-bearing walls of the demolished structure. Table 4 provides various sizes of the specimens. The surface of the specimens is smoothened to eliminate any unwanted residue of building materials. After that, the samples are tested using an NDT apparatus (Fig. 5d–e). Table 4 presents different NDT parameters of these specimens. Thereafter, the samples are tested for compressive strength (Fig. 5f), and data are reported in Table 5.

5 Comparison with different methods

The actual values obtained by experimental testing and the values predicted by the machine learning technique (SVM) are compared to demonstrate the applicability of our proposed method. Several empirical equations have been suggested by various design codes and researchers to predict the masonry compressive strength. The comparison is done by evaluating it with empirical equations available in various design codes for masonry structures. Most of the developed relationships considered the effect of individual brick and mortar strength to predict joint strength of units. However, few of them consider only the strength of brick for estimating masonry compressive strength. The inputs to the SVM model are average NDT parameters obtained for different retrieved blocks are calculated as 32.5 for RH and 2096 for UPV (Table 4)

Table 5 Average prism strength of demolished blocks

Specimen nos.	Dimensions (in cm) L × B × H	Failure load (kN)	Compressive strength (N/mm^2)
MB-1	63.0 × 22.0 × 28.0	421.23	3.03
MB-2	59.0 × 16.0 × 27.0	256.20	2.70
MB-3	60.0 × 27.0 × 20.5	505.24	3.12
MB-4	57.0 × 21.2 × 28.5	342.23	2.81
MB-5	53.5 × 23.0 × 23.5	295.32	2.35
Average		367.42	2.80
SD		100.0	0.30

Table 6 Different empirical formulas for predicting the compressive strength of masonry

S. no.	Empirical formulas	Equation	Average value
a	Mann [3]	$0.83 \times f_b^{0.67} \times f_m^{0.33}$	7.25
b	Hendry and Malek [4]	$0.317 \times f_b^{0.531} \times f_m^{0.208}$	1.60
c	Dayaratnam [5]	$0.275 \times f_b^{0.5} \times f_m^{0.5}$	2.24
d	Benett et al. [6]	$0.3 \times f_b$	3.01
e	Eurocode 6 [12]	$0.5 \times f_b^{0.65} \times f_m^{0.25}$	3.59
f	ACI 1999 [13]	$2.8 + 0.2 \times f_b$	4.80
g	MSJC [7]	$(400 + 0.25 \times f_b)/145$	2.78
h	Kaushik et al. [8]	$0.63 \times f_b^{0.49} \times f_m^{0.32}$	3.57
i	Dymiotis et al. [9]	$0.3266 \times f_b \times (1 - 0.0027 \times f_b + 0.0147 \times f_m)$	3.50
j	Gumaste et al. [10]	$0.225 \times f_b^{0.855} \times f_m^{0.146}$	2.13
k	Garzón-Roca [11]	$0.53 \times f_b + 0.93 \times f_m - 10.32$	1.14

Table 6 summarises the values obtained by the equations suggested by various researchers. The value obtained using SVM model is 2.79 N/mm^2. The lowest difference is obtained between the experimental value and the value predicted by MSJC and SVM. Hence, the current approach (SVM) can estimate the compressive strength of masonry with more accuracy than empirical equations. From the table, it is worth deducing that apart from SVM, models by MSJC [7] and Gumaste et al. [10], give realistic results which are closer to the experimental values (2.80 N/mm^2) obtained using destructive tests. Figure 7 displays a comparison between the predicted and measured values reported in Table 6. The Figure demonstrates an acceptable match between the actual and predicted values. Figure 8a and b reports the comparison between the experimental values obtained from compressive testing in the laboratory with the values predicted by SVM for both training and testing data from the case study. Again, the values closely agree with the experimental test data making the model applicable on-site conditions. Some minor errors can be attributed to incorrect estimation in failure load for masonry blocks, the difference in mortar strength used to reconstruct sample and workmanship. Although, apart from individual variations among the five samples, the average value predicted by SVM closely matches with the value obtained from experimental testing.

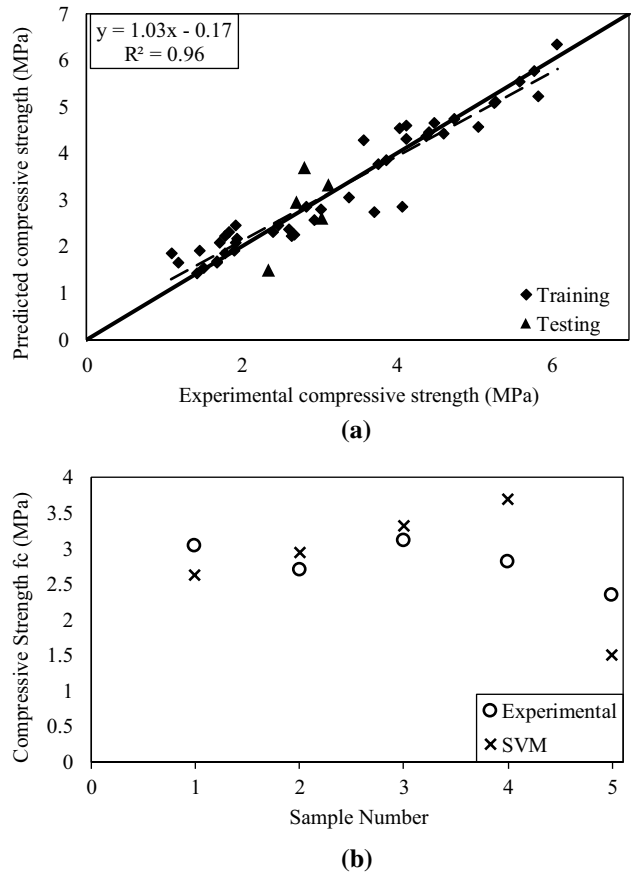


Fig. 8 Comparison of SVM with **a** testing data, **b** experimental samples extracted from the building

6 Conclusion and discussion

In this study, an SVM is developed for estimating the compressive strength of brick-mortar masonry at a building site in Kharagpur, India. The inputs for the model comprise ND tests. The SVM model is developed with an f_b, RH and ultrasonic velocity as inputs and the compressive strength of wallettes as an output for 44 laboratory samples. The model is tested for five datasets by directly obtaining samples at building sites. The compressive strength of masonry buildings is estimated through the analysis of collected data using the SVM. For performance indicators,

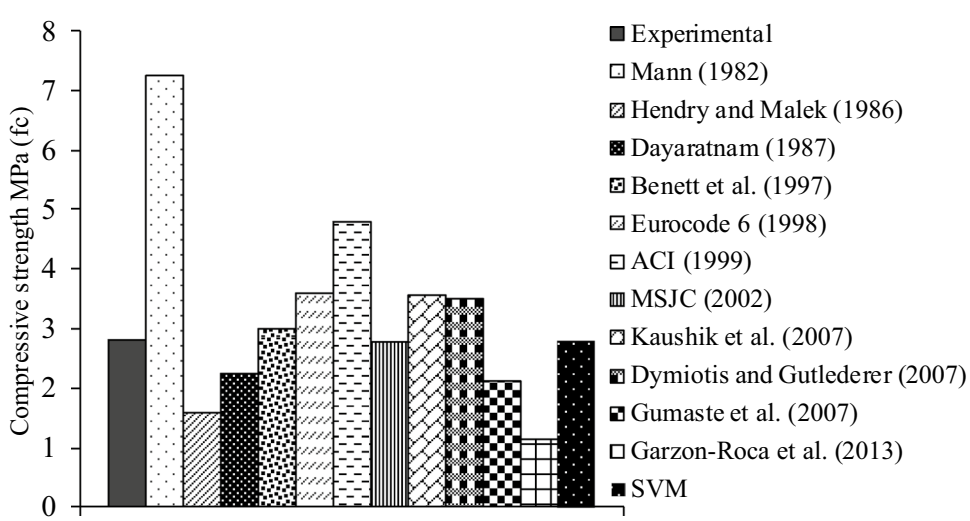


Fig. 7 Comparison of SVM with other models available in the literature

the SVM model generated a coefficient of correlation and root mean square error of 0.980 and 0.589.

The results obtained using the SVM model are considerably consistent with on-site conditions, which are validated using the experimental testing of the extracted samples. The estimated and measured values obtained using the SVM are similar, and thus, the model is satisfactory in predicting the compressive strength of the brick-mortar masonry structure. The SVM model also can take into account the noise associated with NDT measurements in the field via two slack variables ξ and ξ^*. Thus, it can decrease uncertainty in estimation of compressive strength by cancelling the effect of noise in the measurements up-to some extent, which might not be possible in other soft computing techniques such as ANN. Furthermore, empirical formulas used for comparison are primarily based on two parameters, and the sample-specific data is used to derive these formulas. Under actual site conditions, compressive strength changes with time and is influenced by various factors, such as the current damage condition of buildings. Therefore, the developed model must consider indicators that are updated with time. In addition, some sources of error may be observed because of the presence of noise and unreliable data in the data acquisition stage. The proposed approach is advantageous because the on-site NDT results are used to update the model instead of constant indicators, which may not reflect the damage conditions of buildings. The proposed approach can serve as a theoretical guidance for the inspection professionals and practitioners to evaluate structural damage in the field. This will then facilitate timely and appropriate administering of retrofitting technique.

In the future work, the SVM model can be improved by considering more parameters for the input layer for more accurate indicators of the service life of buildings. Furthermore, flat jack tests will endeavour to provide an insight into the joint characteristics of brick mortar masonry that should further assist realistic compressive strength of masonry. After the development of the model incorporating additional parameters, it can be applied to sites for compressive strength estimation. The SVM model can also be compared with commonly used soft computing techniques such as artificial neural networks (ANN) and adaptive neuro fuzzy inference system (ANFIS) to demonstrate its performance against alternative approaches. More input data can be obtained by performing additional experimental tests in the laboratory by varying the dimensions of the masonry wallet, type of bricks and different strengths of mortar. In this way, the model can avoid the problem of overfitting prevalent over limited data sets and hence will improve its accuracy. Furthermore, the parameters of the SVM model, can further be refined by using an optimisation algorithm in order to avoid choosing incorrect values by trial and error method.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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