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ORIGINAL ARTICLE

Reinforced concrete deep beam shear strength capacity modelling using an integrative bio-inspired algorithm with an artificial intelligence model

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Abstract

The design and sustainability of reinforced concrete deep beam are still the main issues in the sector of structural engineering despite the existence of modern advancements in this area. Proper understanding of shear stress characteristics can assist in providing safer design and prevent failure in deep beams which consequently lead to saving lives and properties. In this investigation, a new intelligent model depending on the hybridization of support vector regression with bio-inspired optimization approach called genetic algorithm (SVR-GA) is employed to predict the shear strength of reinforced concrete (RC) deep beams based on dimensional, mechanical and material parameters properties. The adopted SVR-GA modelling approach is validated against three different well established artificial intelligent (AI) models, including classical SVR, artificial neural network (ANN) and gradient boosted decision trees (GBDTs). The comparison assessments provide a clear impression of the superior capability of the proposed SVR-GA model in the prediction of shear strength capability of simply supported deep beams. The simulated results gained by SVR-GA model are very close to the experimental ones. In quantitative results, the coefficient of determination (R^2) during the testing phase ($R^2 = 0.95$), whereas the other comparable models generated relatively lower values of R^2 ranging from 0.884 to 0.941. All in all, the proposed SVR-GA model showed an applicable and robust computer aid technology for modelling RC deep beam shear strength that contributes to the base knowledge of material and structural engineering perspective.

Keywords Shear strength · Structure sustainability · Genetic algorithm · Deep beam · Computer aid models

1 Introduction

Reinforced-concrete (RC) deep beams are structural members that are regularly employed as load distribution elements; they are usually used in foundation walls, folded plate construction, pile caps in transfer girders, and tall buildings [1, 2]. Regardless of popularity and benefit, these beams are tedious in design as a result of the nonlinear effect of different parameters on their properties and shear strength [3, 4]. Shear stress is notably one of the known failure modes of RC deep beams, which generally causes severe failure and loss of life [5]. Over couple decades, quantitative studies have depended on shear strength for the analysis of the behaviour of RC deep beams; this includes the strut-and-tie model [6, 7], and mechanism analysis based on finite element analysis and upper bound theorem of plasticity theory [8, 9]. Meanwhile, these are linear design procedures that often produce estimated values that varied significantly from the actual strength of these beams [10].

In deep beam, the shear strength failure mode is predominant and can cause catastrophic repercussions threatening the safety of buildings. Several studies have been carried out intensively last two decades to disclose and predict the behavior of deep beam in a structural system and discover the most important parameters that affect the shear strength capacity. In accordance to the previous researches, shear strength depends mainly on several factors such as compressive strength of concrete, yield strength of vertical and horizontal reinforcement, ratio of effective depth to breadth, as well as main reinforcement ratio [10–15]. In general, there is a complex relationship between the mentioned variables

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and the shear strength capacity. However, many papers in the literature have been published for accurately predicting the shear strength of deep beam based on classical models such as linear and nonlinear methods [8, 16]. For instance, strut-and-tie method is used widely to estimate shear strength based on two codes called American Concrete Association (ACI) [17] and the Canadian Standards Association (CSA) [18].

Various scholars have come with various design code procedures that aim at the calculation of the ultimate shear strength of RC deep beams [17, 19, 20]. Nevertheless, the obtained values with these procedures, when compared to the values obtained from experimental tests, are conservative at best and subpar at worst. These design codes perform well due to the massive parameters' numbers, as well as the nonlinear relationships that exist between the RC deep beam and the related parameters. The outcome of this relationship is an inherent difficulty in building a model that can accurately perform mathematical shear strength approximation. On top of that, because of the limitation of classical models, the prediction of shear strength is conservative in experimental tests [6, 10]. Thus, the designers are limited in assessing the shear strength as it is extremely difficult to construct an accurate model can estimate the capacity of shear strength accurately based on mathematical equations [21].

The field of artificial intelligence (AI) witnessed a massive research attention in civil engineering over the last few years [14, 22–25]. AI technology has been successfully reported to simulate human inference processes; hence, it has become a robust technique for addressing different engineering issues. Moreover, the means of AI assists scholars and researchers to get a better understanding of the behaviour of complex phenomena in a certain structural system. In the field of structural engineering, it is necessary to understand the behavior of structural elements, especially hybrid sections under the applied loads [26]. Thus, a better understanding of the behavior of these elements is very important for obtaining the best possible and safe designs for the structural sections. However, the casual and empirical equations that used to describe the behavior of the structural sections have defects and limitations. On the contrary, models of artificial intelligence have become a successful alternative to mathematical models due to their ability to capture complex relationships which are difficult to address using traditional methods. Reports exist on the use of AI models can address structural engineering problems. For instance, the study by Adhikary and Mutsuyoshi (2006) focused on the development of two ANN-based models by relying on historical experimental beams data set [27]. The outcomes of the study revealed that the empirical model could not accurately predict the magnitudes of the ultimate shear strength of steel fiber reinforced concrete (SFRC) beams. On the other hand, artificial neural network (ANN) as a branch of AI approaches managed precisely to estimate the SFRC value using fewer input parameters. Another study by [28], authors developed four AI models to simulate the reverse prediction of numerous components of concrete. From the results, a combination of PSO and SVR performed better reverse prediction compared to the other considered AI models. Moreover, the proposed model efficiently minimized the maximum relative error to the lowest value compared to classical models used in the study like ANN, radial basis function ANN, least-square SVM models. Classical AI model of the shear strength squat of RC walls prediction has been developed [29] using the combination of PSO and neural network. The performance of the hybrid model was much better than conventional ANN and empirical models and yielded high accurate predictions. Additionally, the proposed model performed satisfactorily in the shear strength predicting. A prediction model suggested by [30], the scholars used the convolutional neural network (CNN) for predicting the compressive strength of recycled concrete. From the simulation results, the deep learning-based prediction model exhibited higher precision, generalization, and efficiency when compared with the conventional ANN model. Besides, the study carried out by [31] suggested a crack detection method for semantic segmentation of concrete crack images. This model was developed using deep fully convolutional network (FCN) approach. The evaluation of the model showed that it accurately detected concrete cracks and performed accurate crack density evaluation. The adopted mode's performance was excellent and achieved about 90% in average accuracy.

The capability of AI techniques in capturing the complex nonlinear relationship existing between simply supported RC deep beams and the related effective parameters has been demonstrated. For instance, the conducted study by [32] employed the ANN model for ultimate shear strength prediction of RC deep beams. Based on the obtained results, the neural networks were found reliable alternative methods for shear strength capacity prediction of RC deep beams. Another investigation conducted by Mohammad hassani et al. (2013) reported the use of Adaptive network-based fuzzy inference system (ANFIS) for the deflection prediction on high strength self-compacting concrete (HSSCC) deep beams [33]. From the analysis, it was concluded that ANFIS achieved accurate and satisfactory performances. In the study by Cheng and Cao (2014), the hybridization of adaptive regression splines (EMARS) with artificial bee colony (ABC) was proposed [15]. From the results, the hybrid approach was found efficient in the prediction of the shear strength of RC deep beam. Other researchers reported the use of SVR for engineering purposes. They testified its suitability in various tasks, such as the prediction of concrete fracture parameters [34], identification of hysteretic structural system [35], elastic modulus prediction of H–S concrete [36], etc. For instance, Chou et al. (2015) worked on a model that combined a novel smart artificial firefly colony algorithm (SFA) with LS-SVR [11]. The evaluation results showed the efficiency of the prediction model RC deep beam shear strength prediction, as well as its ability to help during the design of RC deep beam structures.

Among several applications of AI approaches, SVR that used in solving civil engineering issues since that approach has lots of advantages such as fast computation and good generalization abilities [11, 37]. However, one major drawback of support vector regression (SVR) model is the tuning of its internal parameters; therefore, the prediction capability of SVR model is generally improved by combining it with natural-based frameworks for tuning such internal parameters [38]. In this study, SVR model is hybridized with a genetic algorithm (SVR-GA) to develop an optimized framework for the prediction of the shear strength of RC deep beams. The aim of integrating the GA is to perform autonomous identification of the optimal parameter settings that will ensure the best performance of the SVR-GA model. The proposed SVR-GA model is evaluated in terms of its performance by benchmarking against three classical models including (SVR, ANN and GBDTs). Also, the current research results are validated against the reported results over the literature studies conducted on the shear strength prediction.

2 Data description

The dataset used in this study was sourced from previously published works that discussed the shear strength of RC deep beams. A total of 217 test records on deep beams were gathered following an extensive review of the existing literature [39–46]. The type of RC deep beam considered in this study is the simply supported beam; the tests were performed until beam failure. The literature review helped in identifying the factors, which influence the shear strength of RC beams [13]. The identified factors include the effective depth (d), main reinforcement ratio (ρ), web width (b), vertical shear reinforcement ratio (ρ_v), compressive strength of concrete (f_c), horizontal shear reinforcement ratio (ρ_h), vertical shear force (V) as well as shear span ratio to effective depth (a/d). In this study, these factors served as the input parameters for the prediction of the shear of the RC deep beam (V/bd). Before using the dataset, it was partitioned into training and testing groups that comprised of 152 tests for the training phase and 65 tests for the testing phase. The details of the RC beam are illustrated in Fig. 1.

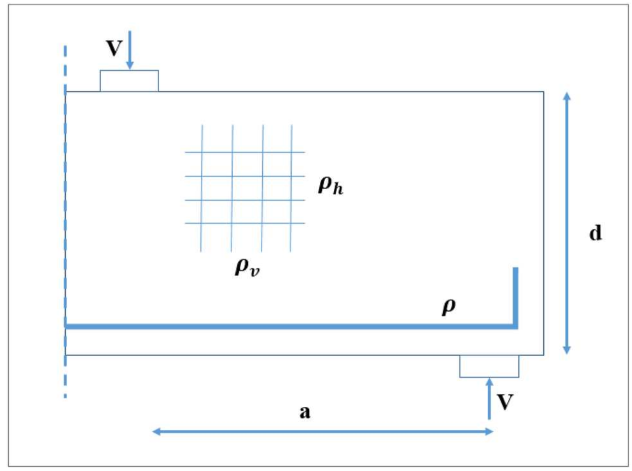


Fig. 1 The explanation of RC beam parameters

3 Applied predictive models

3.1 Supporting vector regression

Recently, many machine learning approaches were developed and SVR one of these approaches to use in various engineering applications [47, 48]. A comparison of the predictive and forecasting accuracy of the SVR showed that it performs better than most of the other existing frameworks, such, as neural network [49]. As per indicated in previous researches, Vapnik developed the SVR depending on statistical machine learning and structural risk minimization [50]. besides, the upper bound error was minimized after developing SVR comparison to local training error minimization as achieved by other ML approaches [51]. The SVR has been significantly improved in the current decade compared to most of the soft computing techniques. The areas of development in the SVR include the presence of the kernel equations that are generally included in most nonlinear transmutations. The nonlinear kernel also has the ability to transfer features and labels to high-dimensional space thereby separating them easily. Another area of improvement is that it confers a convex nature to obtain higher marginal distance thereby, obtaining a unique solution. In general, convex optimization considers a big deal in many applications of AI such as SVR approach. The main goal of SVM algorithm is to efficiently find the hyper-parameters that minimize the objective function. Moreover, the hyperplane is very important and can be calculated using a kernel function. For obtaining more accurate results, the marginal distance should be maximized by the algorithm. Maximizing the marginal distance is considered s unique feature that distinguishes SVR approach from other AI approaches.

The approximation function of SVRs is mathematically represented in Eq. 1 depending on Vapnik's theory.

$$f(x) = w \cdot \varphi(x) + b, \tag{1}$$

$$C = 0.5w^2 + C\frac{1}{n}\sum_{i=1}^{n} L(x_i, d_i). \tag{2}$$

Consider a given range of dataset, $R = \{x_i, d_i\}_i^n$; the term $\varphi(x)$ in Eq. 1 represents the high dimensional space of the input parameter, while w and b are the normal vector and scalar, accordingly. In Eq. 2, the function, $0.5w^2$, represent the standard error while the function, $C\frac{1}{n}\sum_{i=1}^{n} L(x_i, d_i)$, represent the regularization term. The computation of parameters w and b in Eq. 1 is done based on the following minimization function [52]:

$$\mathrm{Min}R_{\mathrm{SVR}}\left(w, \xi^{(*)}\right) = 0.5w^2 + C\frac{1}{n}\sum_{i=1}^{n}\left(\xi_i, \xi_i^*\right), \tag{3}$$

$$\text{Subject to}\begin{cases} d_i - w \cdot \varphi(x_i) + b_i \leq \varepsilon + \xi_i \\ w \cdot \varphi(x_i) + b_i - d_i \leq \varepsilon + \xi_i^* \end{cases} \xi_i, \xi_i^* \geq 0, i = 1, \ldots, 1, \tag{4}$$

where ξ_i and ξ_i^* are the positive slack variables that express over deviation in the upper and lower regions while C represents the error penalty for controlling the trade-off between the empirical error and the regularization term. ε is the loss function related to the approximation accuracy of the training dataset. Based on Eq. 1, the Lagrange and the constraints could be optimally solved using the generic function, and could best be expressed as follows:

$$f\left(x, a_i, a_i^*\right) = \sum_{i=1}^{n}\left(a_i - a_i^*\right)K\left(x, x_i\right) + b, \tag{5}$$

where $K(x, x_i)$ represents the kernel function. Here, the SVR mainly aims at utilizing a nonlinearity method to identify the correlation of data. In nonlinear machine learning, the kernel function could be computed in a simple process. This technique was used for the inner product calculation in feature space as it serves as a function to the original input points. Owing to the capability of the SVR to alter and map information into an HD space, it is suitable for kernel functions. The products of the input space can be characterized by the results achieved from such space. The description of the SVR model is shown in Fig. 2.

One of the most important issues in developing SVR models is to use the proper kernel function. There are four well-known kennel functions called the polynomial, linear, sigmoid, and radial basis functions (RBF) [49]. Over the past year, RBF was the commonly used kernel function owing to its efficiency, reliability, and simplicity. RBF is also adaptable, especially when faced with multiple parameters [53]. The training of the equation of the RBF kernel could be done using just a set of linear functions rather than relying on programming methods that are complicated and lengthy. Hence, this study employed the equation of RBF (with parameter σ); the definition of the nonlinear RBF was based on the prediction accuracy depending on its three factors (C, ε, and γ) selection. The genetic algorithm was utilized to set the optimum values of the three factors.

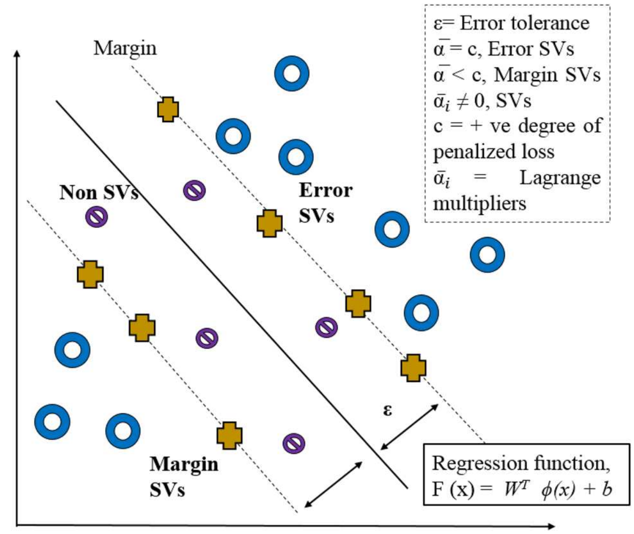


Fig. 2 Graphical description of the SVR model

3.2 The hybridized SVR-GA model

For the last few years, GA has been used as a powerful optimization tool in solving various academic and engineering problems [54, 55]. One unique feature of the GA is that it can find a global optimum solution because it can explore the whole search space using several individuals and concurrently checks the manner of improvement in the constraints and objective function. As a popular approach, the GA is applicable in the optimization of complex problems as it depends on the concept of natural selection [56]. The working principle of the GA relies on multiple iterations of the natural selection process, beginning from the initial population to the last one. In the GA, the selection of individuals in each generation is reliant on the preferable attributes that make them suitable to take part in the generation of the next generation; this process is continuously repeated in all the new generations. However, the low- ranking members of each generation are not selected. Figure 3 presents the structure of the proposed hybrid SVR-GA model. The presence of any surviving low-ranking individuals in a new population improves the diversity of the new population as better solutions can now be found due to the presence of the low-ranking individual.

Meanwhile, the GA does not converge the equal chances of the parents producing the next generation. Furthermore,

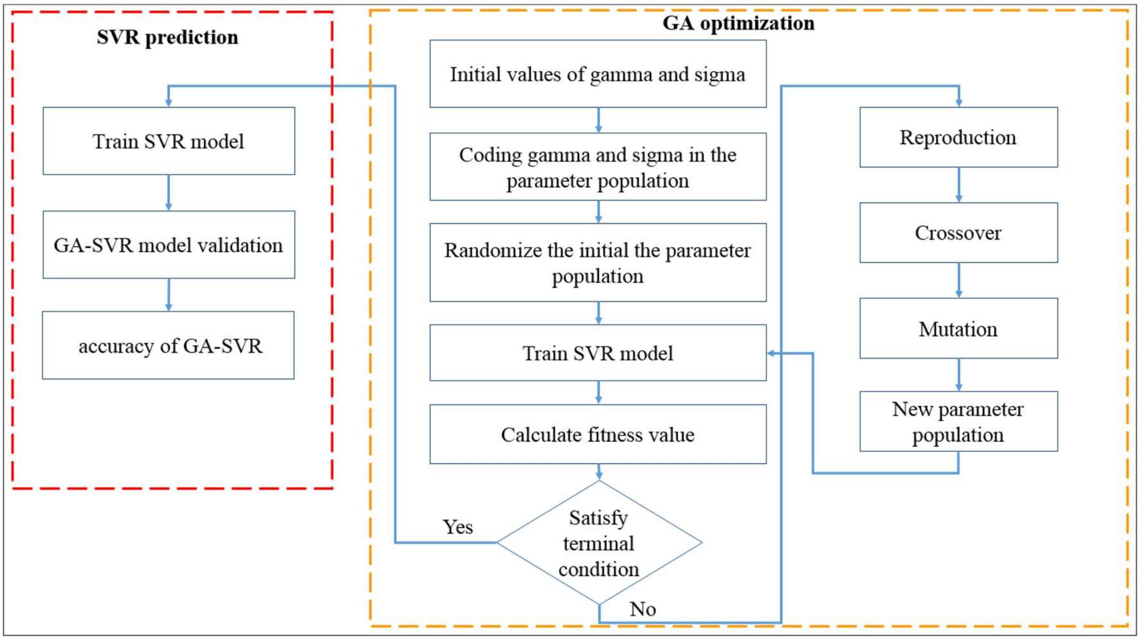


Fig. 3 Structure of hybrid SVR-GA model

the performance of the GA is under the influence of the crossover and mutation operations. Utilization of a low crossover ratio pulls the GA away from most individuals to the optimal point. Regarding the change process, it is used to create new and differentiated individuals who can explore the entire solution area and direct GA to the global cap. The performance of the GA is also affected by other factors, such as the size of the population, the fitness scaling function, the crossover function, the selection function, and the mutation function.

3.3 The model of artificial neural network

The robustness of ANN model in handling nonlinear data and providing a solution to complex problems made them one of the popular AI models [57]. The ANN model was first developed by [58], and since its development, it has kept on evolving; its efficiency is related to the choice of the appropriate input techniques during its training. The ANN architecture is comprised of 3 main layers—output, hidden, and input layers; the layer's number increases with the complexity of the problem. The training process of ANN is implemented using various learning algorithms. ANN is an efficient tool because of its capability of using an input significance approach for the determination of the likely input for the output parameters [59, 60]. ANNs are modelled after the human brain in terms of functionality; each of the three ANN layers contains a specific number of neurons [61]. The ANN can approximate both linear and nonlinear functions and can also implement piece-wise functions approximation. The implication is that ANNs are suitable for building non-linear piece-wise models. ANNs made with one or more hidden layers can effectively separate the space in different areas and establish different functions for each space. The structure of the ANN algorithm is presented below:

$$N - H_1 - H_2 - \cdots - H_{\mathrm{NHL}} - M, \tag{6}$$

where N denotes to the input neuron, H is the hidden layers' number in a neural network, and M is the predicted variable. Equation 7 can calculate a hidden layer.

$$v_i = \left(1 + \exp\left(-1 \times \sum_{i=1}^{1} x_i w_{ij}\right)\right)^{-1}, \tag{7}$$

where v_i denotes to the hidden layer, x_i is the input variable, and w_{ij} represents the weight between the layers. The value of the output layer is calculated as below:

$$y = \left(1 + \exp\left(-1 \times \sum_{j=1}^{1} v_j w_{ij}\right)\right)^{-1}. \tag{8}$$

There are two necessary steps involved in forecasting with neural networks; these are the training and learning phases. The feedforward networks are normally trained in a supervised approach [62, 63]. A training set is presumed to be available depending on the provided historical data that contains the inputs and the associated expected outputs that is presented to the network. The success of the training phase is dependent on the proper selection of the inputs for the NN. During the learning phase, the input–output mapping is first constructed by the NN, followed by the adjustment of the biases and weights at each iteration by minimizing the error measure between the achieved output and expected output. Therefore, the learning process can be considered an optimization process; this process is continued to minimize the error until an acceptable convergence criterion is reached. The error between predicted and actual values is presented below:

$$\text{Error} = 0.5(d - y)^2, \tag{9}$$

where d represents the actual value, and y is the value of prediction obtained from the algorithm. The feedforward network in this study was trained using backpropagation; the network has one hidden layer, and because of its validity in the regression process, it was used with a sigmoid activation function. Figure 4 illustrated the topology of the ANN model.

3.4 Gradient boosted decision trees (GBDTs)

GBDT aims to upgrade the single model regression performance via the combination of various fitted models. And this implies that GBDT relies on two algorithms (the regression tree is contributed by the DT group, while gradient boosting is a common meta-learning framework for the combination of single RT models.

As a decision support tool, the DT relies on a tree-like model to reach decisions [64]; hence, it is commonly used in data exploration, prediction, and description [65]. It is considered one of the popular models due to its numerous advantages, such as easy information handling visualization, highly flexible in terms of the predictor variables, and simple manner of predictor variables handling at various measurement scales. In addition to that, the capability of handling predictor variables that contain missing values and minimal sensitivity to the presence of outliers. Notwithstanding these numerous advantages, there are two basic weaknesses of DT; the first one is that its predictive performance could be poor in comparison to other approaches such as SVR and ANN. Hence, there is a need for more advanced approaches such as GBDT and RF, which have been proposed recently to address this weakness. The second weakness of DT is that it is difficult to interpret its results when building large trees as its process includes the tree generation and its subsequent pruning.

In a DT model, a root node is normally involved, and this root node contains all the data. This root node is constitutively partitioned into subsets based on certain rules in

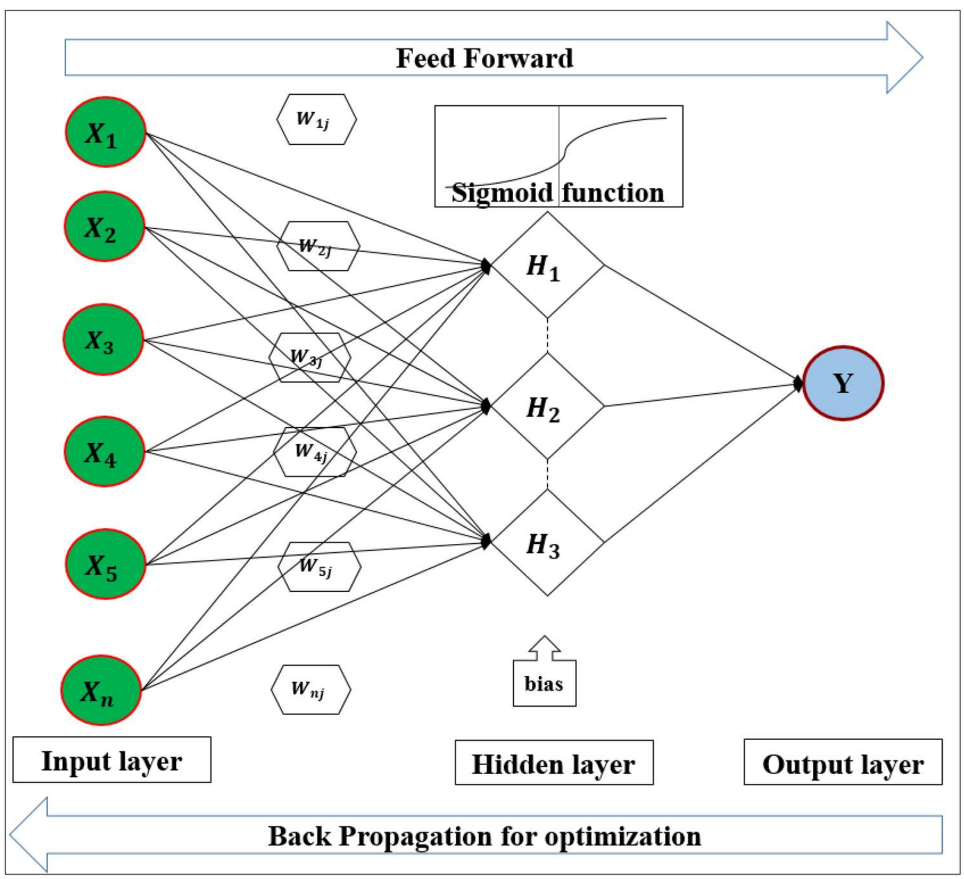


Fig. 4 The ANN model structure

a manner that the sample characteristics are as unique as possible within each subset and differs significantly from the members of the other subsets. The partitioning is continued until a termination criterion is reached. At the end of the DT, the nodes are marked as leaf nodes and will be fitted to the sample mean in the related leaf node for regression tasks.

It is more convenient to find the average of numerous simple rules compared to finding a single rule, boosting, a highly accurate rule is being proposed here for the combination of the rough rules for model performance improvement [66]. The booting process involves fitting of simple models to the data of training to steadily increase the performance of the model on specimens that are yet to be predicted accurately by the currently existing models. Regarding regression tasks, the boosting begins with the differentiable loss function selection; the whole gradient is boosting process is aimed at how to minimize this function. Hence, the first RT can be built in a manner that will ensure maximum reduction of the loss function. The mathematical representation of GBDTs is shown below:

$$F_m(X) = F_{m-1}(X) + h_m(X), \tag{10}$$

where $h_m(X)$ refers to the weak decision tree and $F_m(X)$ is the summation of that learner. With the incorporation of sequential RT, which may differ structurally from the first one, the loss residuals function can be minimized from the obtainable trees. This process is implemented in stages while the existing trees are kept intact while adding the following trees.

$$F_m\left(X_i\right) = F_{m-1}\left(X_i\right) + h_m\left(X_i\right) = Y_i, \tag{11}$$

$$h_m\left(X_{i,t}\right) = Y_{i,t} + F_{m-1}\left(X_{i,t}\right), \tag{12}$$

$$F_m(X) = F_{m-1}(X) + vh_m(X)v \in [0;1], \tag{13}$$

where m represents the number of iterations, and h_m refers to the presented model at iteration, v is the learning rate in the gradient descent process. Finally, all the single RT built during the gradient boosting process are combined to obtain the final GBDT model, whose accuracy and robustness cannot be matched with those of the single DT models [67].

4 Modelling development and performance metrics

The dataset used for constructing forecast models, including 217 test records on deep beams were gathered from previous studies. Four predictive models have been developed in this study called SVM, ANN, GBDTs, and SVR-GA. The bio-inspirited algorithm (GA) was used to optimally tune the hyper-parameter of SVR model. The input variables that used to develop the models included different geometrical, material and physical factors such as the effective depth (d), main reinforcement ratio (ρ), web width (b), vertical shear reinforcement ratio (ρ_v), concrete compressive strength (f_c), horizontal shear reinforcement ratio (ρ_h), besides shear span ratio to effective depth (a/d).

The capacity of shear strength in deep beams largely depends on the shear span ratio (a/d) factor. Numerous scientific studies illustrated that the a/d parameter has the most significant effect on the shear strength capacity in deep beam [3, 43, 68, 69]. These studies proved that the magnitude of shear strength increases as a/b decreases. The reason is that when the a/b ratio is decreased, the load is transferred by concrete struts formed as a result of diagonal cracks directly to the supporters. Among all mentioned input parameter, concrete compressive strength (f_c) parameter has also a significant influence on shear strength capacity. El-Sayed et al. [70] conducted a study and illustrated that strength capacity increased up to 10% if f_c increased by 45%. The third parameter is effective depth (d) which has an adverse effect on shear strength. The shear strength capacity is decreased if the depth of beam increases. Yang et al. [71] carried out a study to investigate the characteristic of shear strength using 21 beam specimens with different parameters beam depth. The study revealed that an increase in beam depth leads to more brittle failure in beams accompanying with wide diagonal cracks.

Several studies proved that the main reinforcement parameter has an effective impact on the shear strength in deep beams. Mau and Hsu (1989) [72] carried out a study to investigate the effect of main reinforcement on shear strength. There were 64 experiments conducted on depth beams and found that the shear strength capacity increases significantly with an increase in longitudinal reinforcement. In literature, several studies proved that the longitudinal reinforcement parameter has a linear correlation with shear strength capacity up to a specific limit [68, 69]. Finally, the web depth parameter is considered one of the most important factors that significantly affect the shear strength capacity aside a/d ration. Several scientific studies illustrated that the shear strength capacity of depth beams linearity increases with the increase of vertical web reinforcement [16, 41, 46].

70% of the dataset (152 samples) used to model construction and the rest (65 samples) utilized for validation purposes. It is important to mention that RapidMiner software was used for the construction of all applied predictive models [73]. To assign the best predictive modelling approach, five statistical measures used in this current study which are: root mean square error (RMSE), mean absolute error (MAE), correlation of determination (R^2), Willmott-Index (WI) and Nash-Efficiency coefficient (NE). The formula of these statistical criteria can be shown below [74, 75]:

$$\mathrm{MAE} = \frac{1}{N}\sum_{i=1}^{n}\left|\left(\mathrm{SSCobs}_i - \mathrm{SSCprd}_i\right)\right|, \tag{14}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(\mathrm{SSCobs}_i - \mathrm{SSCprd}_i)^2}, \tag{15}$$

$$\mathrm{NE} = 1 - \left[\frac{\sum_{i=1}^{n}(\mathrm{SSCobs}_i - \mathrm{SSCprd}_i)^2}{\sum_{i=1}^{n}(\mathrm{SSCobs}_i - \overline{\mathrm{SSCobs}})^2}\right], \tag{16}$$

$$\mathrm{RE\%} = 100 \times \frac{\mathrm{SSCobs}_i - \mathrm{SSCprd}_i}{\mathrm{SSCobs}_i}, \tag{17}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\mathrm{SSCobs}_i - \mathrm{SSCprd}_i}{\sum_{i=1}^{n}\left(\mathrm{SSCobs}_i - \mathrm{SSCprd}_i\right)^2}, \tag{18}$$

$$\mathrm{WI} = 1 - \left[\frac{\frac{1}{N}\sum_{i=1}^{n}(\mathrm{SSCobs}_i - \mathrm{SSCprd}_i)^2}{\sum_{i=1}^{n}(\left|\mathrm{SSCprd}_i - \overline{\mathrm{SSCobs}}\right| + \left|\mathrm{SSCobs}_i - \overline{\mathrm{SSCobs}}\right|)^2}\right], \tag{19}$$

SSCobs_i and SSCprd_i are observed and forecasted ith values of shear strength capacity (SSC), $\overline{\mathrm{SSCobs}}$ and $\overline{\mathrm{SSCprd}}$ represent the average SSC of observed and predicted in a trained and tested sample set, n refers to the total number of experimental samples.

5 Results discussion and analysis

Accurate and reliable prediction of shear strength of the deep beam is essential in structural engineering. A newly developed hybrid intelligent model called SVR-GA is proposed for this purpose. Three well-established AI predictive models were employed in this study for validation to the shear strength of RC deep beams predict, including classical SVR, ANN and GBDTs. Different statistical measures such as RMSE, MAE, NSE, WI, and R^2 were computed for assessing the performance of each predictive model. Depending on the reported statistical results in Table 1, the SVR and SVR-GA models perform well during the training phase and recorded higher values of R^2 and WI and the lowest values of MAE and RMSE. However, the performance of the other two models ANN and GBDTs are very poor according to statistical criteria. Moreover, the classical algorithm that used to train the standard predictive model (SVR) generally minimizes the sum square error. On the other hand, the bio-inspired algorithm used in this current study has two main advantages. The first one is to minimize the sum square error during training set and the second one is to optimally calculate the hyperparameters of SVM which play an important role to provide the predictive model with the capability to generalize and prevent overfitting issue. The correlation of determination (R^2) usually scales between 0 and 1, however, the RMSE criteria cannot be limited to a specific range. Moreover, all statistical metrics mentioned in Table 1, except R^2 values are strongly influenced by outliers and sometimes provide misleading evaluations. For instance but not limited, the values of RMSE and MSE parameters are completely different if they are calculated after or before the de-normalization process. On the other hand, the R^2 value remains constant and does not change with the change in the scale of the data. For instance, the values of those statistical parameters for any model during the training process where all data are within a specified range, the calculated values of those parameters are very small, but when the data is returned to its normal range, the values of these statistical parameters have changed significantly.

Nevertheless, the training phase cannot provide an adequate assessment because of the models in this phase, trained by known targets. Therefore, the testing stage is the crucial stage in assessing the efficiency of the model because the unseen target data are introduced; thus, the generalization efficiency of the model can be revealed. In accordance with tabulated results in Table 1, the ANN and GBDTs

Table 1 The indicators of prediction performance skills for the applied predictive models overtraining and testing phases

Models	RMSE	MAE	R^2	NSE	WI
Training phase					
SVR	0.029813	0.01702	0.977874	0.977606	0.9943082
SVR-GA	0.03128	0.020778	0.970079	0.975349	0.9910029
ANN	0.068653	0.052368	0.865494	0.881251	0.9515345
GBDTs	0.044235	0.180615	0.948042	0.9507	0.9807319
Testing phase					
SVR	0.039842	0.030912	0.940614	0.929312232	0.983036904
SVR-GA	0.04073	0.031229	0.958157	0.926125484	0.98081133
ANN	0.070213	0.057019	0.884346	0.780473902	0.936358171
GBDTs	0.056998	0.158517	0.934895	0.85533302	0.956274751

models, respectively, recorded the worst accuracy prediction in terms of RMSE (0.0702 and 0.0570), R^2 (0.884, 0.935), and MAE (0.057, 0.159). However, the SVR and SVR-GA, respectively, exhibited the best accuracy prediction and recorded very low RMSE (0.04, 0.041), MAE (0.031, 0.031), and higher values of NSE (0.926, 0.626), and WI (0.983, 0.981). Although there is a good similarity in prediction shear strength capacity between both models according to four statistical indicators, the R^2 criteria are crucial. They can provide decisive information that helps to select the best predictive models. Table 1 illustrated that the SVR-GA provided high accurate results in terms of correlation of determination ($R^2=0.958$) while classical SVR recorded the second-highest value of ($R^2=0.941$).

The applied predictive models were assessed using the feasibility of correlation analysis. Scatter plot is one of the informative graphical presentations for examining the aptitude of prediction models. Based on the exhibited results in Fig. 5, the scatter plots indicated the ideal correlation over the testing phase for the developed SVR-GA model. This model was followed by SVR, GDBTs and finally ANN model. SVR-GA model manages to predict all the magnitudes of the shear capacity of the RC deep beam. The determination coefficient value of the SVR-GA model reported as the ($R^2=0.958$).

Obtaining a sufficient and more informative graphical evaluation error prediction. The relative error (RE) percentage is calculated for every single observation over the testing

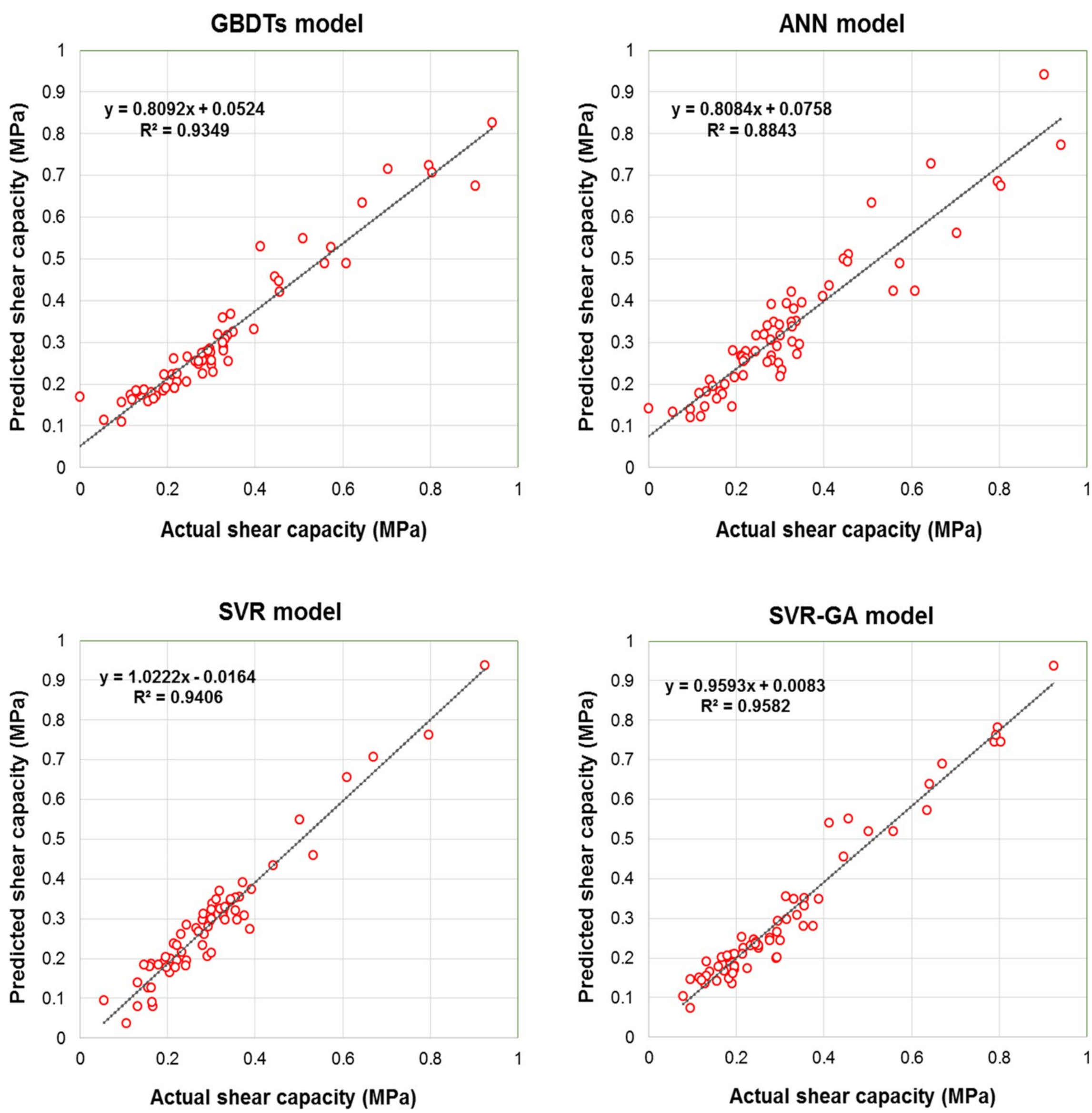
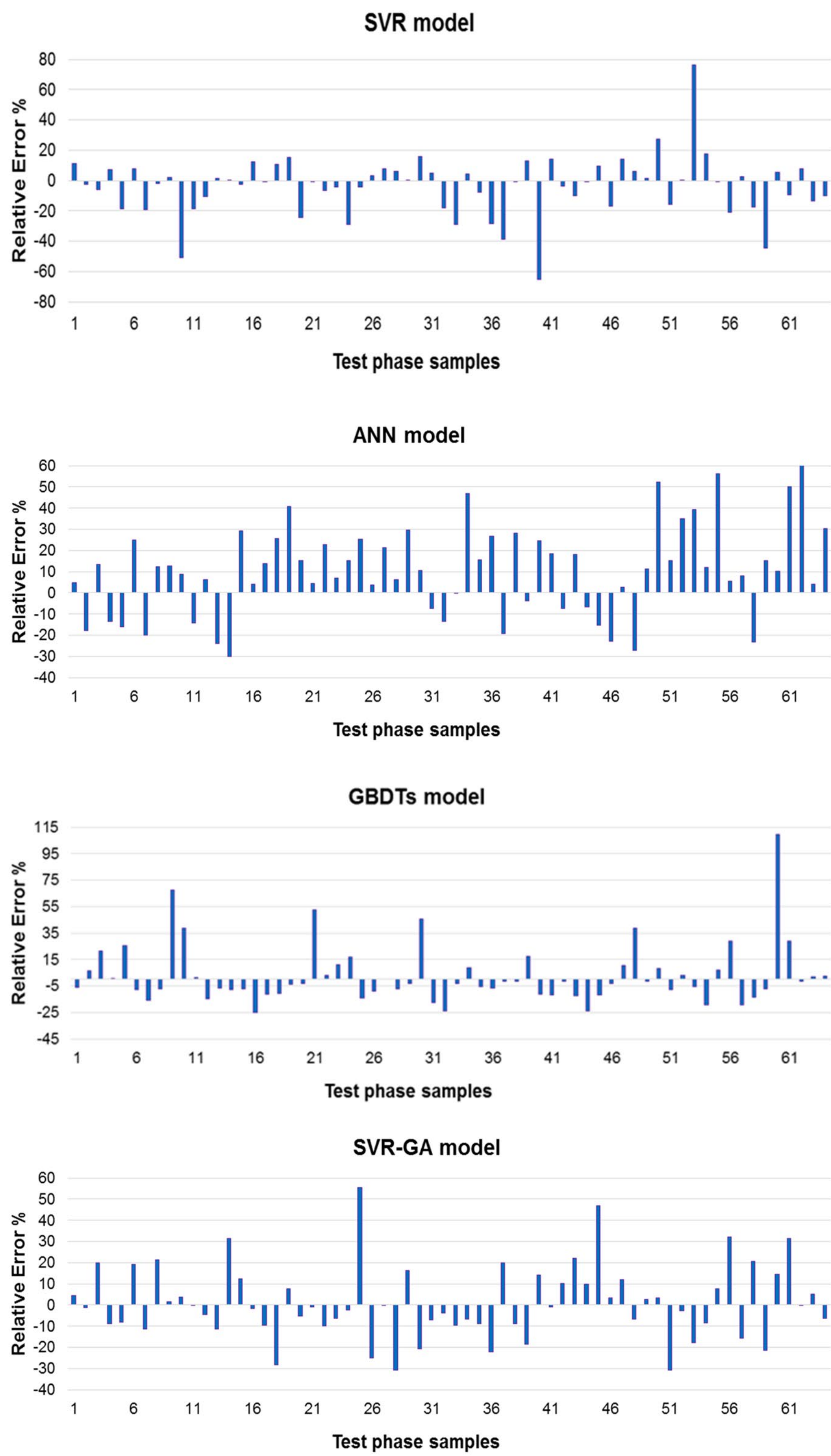


Fig. 5 Scatter plots demonstration between actual shear strength and predicted values obtained from AI models

phase (Fig. 6). The RE value can give an essential meaning for the capacity of the predictive models where how possible to predict the shear capacity of the RC deep beam. Based on the displayed results in Fig. 6, SVR-GA model produced more than 70% of the dataset over the testing phase with limited RE% ranged between (− 10 to 10%). Two observations indicated a RE% exceeds the 40% of error. This result could be due to the absence of the related information over the training dataset to mimic the actual magnitude of those two observations. However, Fig. 6 provides a range of RE%

Fig. 6 Relative error-index over the test phase sample for predicted values utilizing AI models



varied between ∓20% with two observations surpass ∓60% for the SVR model. The GBDTs model indicated good results as well based on the RE% graph; however, a single observation of the testing dataset exceeds 95%. The worst model, based on the RE% evaluation, was observed using the ANN model.

For detailed comparisons, Tayler diagram as shown in Fig. 7, provides a realistic vision of how computed shear strength values match with actual ones following two important statistical metrics (i.e., standard deviation, RMSE and correlation coefficient). This figure presents how the predicted values of AI model are closed from the actual values of shear strength. Graphically, this figure clearly illustrates the effectiveness of developed models and visualizes a series of points on a polar plot. Besides, the variance ratio is computed to generate the relative depth of the predicted and actual variations. The results show that the SVR-GA is closer to the observed point in comparison with the other three predictive modelling approaches (GBTs, SVR, and ANN).

It is an essential aspect to highlights the reliability and accuracy of the suggested SVR-GA model in predicting the beam shear strength capacity of the reinforced concrete deep beam against the established researches over the literature studies. In this regard, the obtained results by SVR-GA model over the testing phase are validated against several predictive models conducted by several researchers in the literature. Prayogo et al. (2019) employed a symbiotic organism search (SOS) algorithm as an optimizer to compute the hyperparameters of SVR and least-squares support vector machine (LS-SVM) [76]. Among the six novel models, the optimized SVM adaptive ensemble weighting (OSVM-AEW) and multiple linear regression and regression tree (MLR-RegTree) showed the best accuracy of performances. Generally, the coefficient of determination (R^2) values varies from 0.838 to 0.922. It is vital to mention that the proposed model of this study SVR-GA generated much more accurate results in comparison to those models (see Fig. 8).

Further, this compression is very important to examine the reliability of SVR-GA model because of all of these modelling-approaches developed using the same dataset. In another investigation carried out by Gandomi et al. (2013) to predict the shear strength of RC deep beams using a hybrid model depending on simulated genetic annealing (SGA) [13]. The result of the quantitative assessment revealed that the GSA model had generated acceptable accuracy within $R^2 = 0.876$ over the testing set. Recently, there are important endeavours taken place to develop novel and reliable predictive modelling approaches to forecast shear strength of deep beams. Among the novel models, Chou et al. (2015) managed to accurately develop a hybrid artificial intelligence model by integrating smart artificial firefly algorithm (SFA) with LS-SVM [11]. The novel SFA algorithm integrated three different approaches, namely, firefly algorithm (FA), chaotic map (CM), Levy fight (LF), and adaptive inertia weight (AIW). The main goal of using the SA algorithm is to accurately compute the hyperparameters of the LS-SVM, thereby improving the model precision. The study achieved high accuracy of prediction, and the R^2 indicator reached 0.938. Finally, it is important to review the empirical modelling approaches executed by some scholars according to traditional codes [i.e., American concrete institute (ACI) and the Canadian Standard Association (CSA)]. According to the

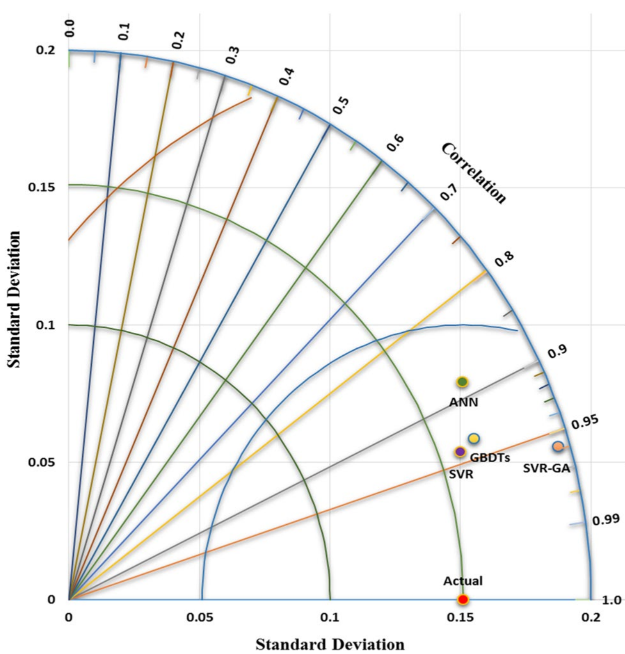


Fig. 7 Taylor diagram presentation for the predicted values of shear strength utilizing AI models

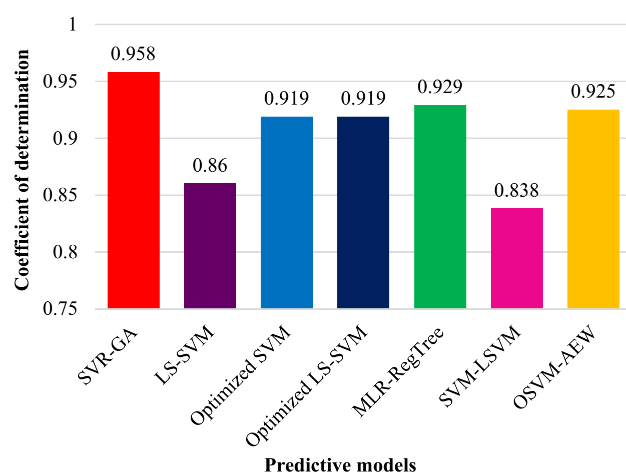


Fig. 8 Comparison between hybrid SVR-GA and the developed predictive models over the literature

statistical measures, the artificial models, in general, provided fewer predicted errors compare to empirical models that are done based on traditional codes. For instance, the two empirical models developed based on ACI and CSA codes provided relatively higher values of statistical errors [76]. The MAE values of both models executed based on ACI and CSA codes, respectively, are 2.06 and 1.632. However, the worst model accuracy in this current study shows better accuracy prediction compared to both mentioned models and produces only 0.159 value of MAE indicator. It is obvious from this survey that the proposed model of this study (SVR-GA) shows better prediction performance of shear strength of RC deep beams in comparison with several robust modelling approaches and yield the highest value of R^2.

The current research results evidenced the potential of tuning the internal parameters of the SVR model and provide a reliable and robust predictive model for RC deep beam shear capacity. The hybridization of the genetic algorithm as a robust nature-inspired optimization algorithm provides a remarkable solution for the hyperparameters AI associated problem.

6 Conclusion and remarks

Since the deep beams are tedious to design, this current study investigates the ability of using a hybrid model (SVR-GA) as a predictive model to estimate the shear strength capacity of RC deep beams. For enhancing the accuracy of the proposed model, the bio-inspired algorithm (GA) is used to find a global solution by efficiently selecting the optimal SVR parameters. To observe the accuracy of the suggested model (SVR-GA) of this study, the model compared with different modelling techniques such as classical SVR, ANN, and GBDTs. The SVR-GA outperformed other compared models, and the R^2 value indicator equaled to 0.958. Moreover, further analyses carried out to assess the reliability of SVR-GA model by comparing its targets with different novel models done by several researchers in literature. Although some of these modelling approaches are novel and perform well, the proposed model of this study (SVR-GA) successfully managed to produce highly accurate predictions and achieved the highest R^2 value. The excellent performance of the employed predictive model is due to the presence of GA, which has a significant role in properly selecting the SVR coefficient.

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Compliance with ethical standards

Conflict of interest The authors declare no conflict of interest.

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