PREDICTION OF PUNCHING SHEAR STRENGTH USING METAHEURISTIC APPROACH OF OPTIMIZATION

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ABSTRACT

The relationship between technology and application of civil engineering is not a new concept. Over the years civil engineering has encountered a slew of issues, most of them have been solved with the aid of technology. Prediction of punching shear strength is one such problem statement which could be solved using a metaheuristic approach of optimization. Numerous experiments on the punching shear resistance of reinforced concrete slabs have been conducted by researchers, with positive findings. The actual service life will be shortened due to steel bars' propensity for corrosion. The main goals of all organizations are to make civil engineering applications more valuable intrinsically so that people can use them to construct faster so that resources are used more effectively, and to ultimately improve people's lives. Using evolutionary artificial neural networks, internal flat slabs of reinforced concrete can be predicted for their punching shear strength. It is a hybrid model of an artificial neural network (ANN) and a Genetic algorithm, a metaheuristic based on natural selection that is a subset of the larger category of evolutionary algorithms (EA). The experimental findings from 519 flat slabs tested by various authors starting in 1938 were used in this research. The model tries to predict the dependent feature, Punching shear resistance, using independent features such as Shape of the column cross section, Column side or smaller side, Larger side of the column, Average effective depth in X and Y directions, Average reinforcement ratio in X and Y directions, Column effective width, Effective width / Effective depth, Concrete compressive strength, and Steel yield strength. Sometimes, signals are altered at the receiving synapses, and the processing element adds the weighted inputs. Input from one neuron is sent to another (or output is sent to the outside world) if it reaches the threshold, and the cycle continues. The algorithm builds the subsequent population at each stage using members of the current generation. By using Selection, Crossover and Mutation, we can obtain a set of optimal parameters that aid in producing effective results. We also contrasted the accuracy attained using GA with other popularly employed optimizer types like SGD, ADAM and RMSProp. We have also made use of the benefits of the GA algorithm, such as its adaptability, understanding ability, and lack of computational complexity.

KEYWORDS

Artificial Neural Network, Reinforced Concrete Flat Slab, Punching Shear Strength, Genetic Algorithm & Metaheuristic.

1. INTRODUCTION

The world has been progressing on every front and civil engineering has a crucial role to play in it. There are slew of processes which are used as lethal application in the construction domain such as: Reinforced concrete slabs[1] are one of the common horizontal load-carrying members in civil engineering, and widely applied in bridges, ports and hydro-structures. Since there is no beam in the flat slab under longitudinal load, the punching failure of reinforced concrete slab occurred easily. Many researchers have carried out numerous experiments on the punching shear resistance[2] of reinforced concrete slabs, and obtained successful results. However, steel bars[3] are prone to corrosion, which will result in the shortening of the actual service life. In recent years, with application of technology across all domains, the durability of structure is one of the prime needs of people. For coastal areas and the areas which consist of usage of chlorides such as dicing salt, the actual service life of structures is often much lower than their design service life, resulting in massive losses of resources. Fiber reinforced polymer (FRP) [4] is a material which has many advantages such as light, high strength and corrosion resistance. In a corrosion environment, to solve the problem of short actual service life of structure, FRP bars [5] can be applied as an alternative to steel bars in concrete structures.

Regarding theoretical models, the majority of the computational formulas for punching shear strength of FRP rein- forced concrete slabs were obtained from conventional rein- forced concrete flat and modified to take FRP into account.

ACI 318-14 and GB 50010-2010 are two current design requirements that use the eccentric shear stress model [6] as its theoretical foundation. A number of mitigation measures have been taken by organizations working across the application of civil engineering such as Large, industrial constructions, parking garages, warehouses, high-rise buildings, and hostels are the main applications for flat slabs [7] . They are employed in situations when beamers are not necessary or in structures with less framework that don't require beamers.

The major objective of all the organizations are to increase the intrinsic value of the civil engineering applications so that people can use it, reduce the time in terms of building it for the purpose of making use of the resources efficiently and eventually creating an impact on the lives of people. However, during theoretical derivations, the aforementioned empirical models incorporated some simplifications; as a result, the empirical models were unable to take into account all of the significant aspects. Furthermore, typical regression analyses using data from experiments were used to establish the parameters in the aforementioned empirical models. As a result, the choice of theoretical models and the calibre of the databases have a significant impact on the models' correctness. Some algorithms containing data at their core have surfaced recently with the advancement of artificial intelligence [8]. Among these algorithms, machine learning has attracted the most research attention [9].

Failure to punching shear strength is due to a strong localized impact, which results in reinforced flat slabs and foundations collapse. This catastrophic collapse generally happens at the borders of the columns. Significant cracks occur during failure [10] . Due to its catastrophic character, it must be prevented; making the determination of the slab's punching shear strength important [11].

In this paper, ANN [12] has been used for the purpose of learning the patterns in the given data efficiently, assisted by loss function and optimizer. In order to further improve the solution, genetic algorithm had been used as an optimizer which in turn is reducing the amount of time for building applications of civil engineering, accuracy of development is being improved.

2. RELATED WORK

Sujith Mangalathua ,Hanbyeol Shin, EunsooChoic, Jong- Su Jeon, titled , "Explainable machine learning models for punching shear strength estimation of flat slabs without trans- verse reinforcement" [13].

It explains the significance and contribution of the components that affect the punching shear strength in the extreme gradient boosting model using the SHapley Additive Explanation approach. To find the best prediction model for the punching shear strength of flat slabs, this study takes into ac- count seven machine learning techniques in addition to linear regression, including ridge regression, support vector regression, decision trees, K-nearest neighbours, random forests, adaptive boosting, and extreme gradient boosting. The associated coefficient of variation for the extreme gradient boosting model is 0.09, while the model's coefficient of determination is 0.98.

Yuanxie Shen, Linfeng Wu, Shixue Liang paper, titled, "Explainable machine learning-based model for failure mode identification of RC flat slabs without transverse reinforcement" explained that for determining the failure mechanism of flat slabs, an accurate prediction model is built by screening 8 machine learning-based models (LR, ANN, DT, SVC, RF, AdaBoost, GBDT, XGBoost). [14] SHAP provides an explanation for the XGBoost prediction, with the findings encompassing both general and specific interpretations as well as the feature dependency relationship between input variables. The best model is XG- Boost, whose precision; recall, F1 score, and accuracy are, respectively, 97.30.

Shasha Lu, Mohammadreza Koopialipoor , Panagiotis G. Asteris , Maziyar Bahri ,Danial Jahed Armaghani paper, titled, "A Novel Feature Selection Approach Based on Tree Models for Evaluating the Punching Shear Capacity of Steel Fiber-Reinforced Concrete Flat Slabs".

This work uses tree predictive models, including random forest (RF), random tree (RT), and classification and regression trees, to create a new model that can predict the punching shear capacity of SFRC flat slabs (CART). It also made use of a cutting-edge feature selection (FS) method. The experiments' findings showed that the FS-RT model performed better in terms of prediction accuracy than the FS-RF and FS-CART models. According to measurements of R2 and RMSE, which ranged from 0.9476 to 0.9831 and 14.4965 to 24.9310, respectively, the FS-RT hybrid approach performed the best in this regard. The three hybrid approaches presented in this work, FS-RT, FS-RF, and FS-CART, were found to be applicable for forecasting SFRC flat slabs.[15]

Duy-Thang Vu , Nhat-Duc Hoang, paper, titled, "Punching shear capacity estimation of FRP-reinforced concrete slabs using a hybrid machine learning approach" explained To develop a new model that can forecast the punching shear capacity of SFRC flat slabs, this work used tree predictive models, including random forest (RF), random tree (RT), and classification and regression trees (CART). It also used a novel feature selection (FS) technique and in comparison to the formula-based and Artificial Neural Network techniques, the new model has reduced Root Mean Squared Error by around 55 and 15.The model employs the least squares sup- port vector machine (LS-SVM) to discover the mapping be- tween the influencing factors and the slab punching capacity. Furthermore, the firefly algorithm (FA), a population-based metaheuristic, is utilized to facilitate the LS-SVM training.[16]

Nhat-DucHoang, paper, titled, "Estimating punching shear capacity of steel fibre reinforced concrete slabs using sequential piecewise multiple linear regression and artificial neural network". This study uses artificial neural networks (ANN) and piecewise multiple linear regression (PMLR) to build a prediction model that can roughly translate the mapping function between the punching shear capacity of SFRC flat slabs and its affecting parameters. The Levenberg-Marquardt backpropagation technique and gradient descent algorithms are used to train the ANN-based prediction models. This data set is then used to train and verify the sequential PMLR (SPMLR) and ANN models. Experimental results show that SPMLR can deliver prediction outcome which is better than those of ANN as well as empirical design equations.[17]

Gamze Dog˘an Musa Hakan Arslan , paper, titled, “Determination of Punching Shear Capacity of Concrete Slabs Reinforced with FRP Bars Using Machine Learning” It stressed on prediction models were developed for the punching strength of the slabs by using the relevant algorithms in five different machine learning techniques (Multiple Linear Regression), Bagging-Decision Tree Regression, Random Forest Regression, Support Vector Regression and Extreme Gradient Boosting (MLR, Bagging-DT, RF, SVR, XGBoost).[18] The best results were achieved by the SVR among the five different algorithms. SVR achieved a predicted success for the strength of slabs produced with GFRP bars. After analysis, R2 values, MAE and RMSE performance metrics were found to be well above the empirical correlations with 96.23.

Table 1. Related works.

Author	**Paper Title**	**ML Model Used**	**Techniques Employed**	**Result**	**References**
Sujith Mangalathua ,Hanbyeol Shin, EunsooChoic, Jong-Su Jeon	Explainable machine learning models for punching shear strength estimation of flat slabs without transverse reinforcement	Linear regression, Ridge regression, support vector regression, decision tree, K-nearest neighbors, random forest, adaptive boosting, and extreme gradient boosting	Used explainable machine learning techniques like SHAP	Extreme gradient boosting model has a coefficient of determinati on of 0.98, and the associated coefficient of variation is 0.09.	[13]
Yuanxie Shen, Linfeng Wu, Shixue Liang	Explainable machine learning-based model for failure mode identification of RC flat slabs without transverse reinforcement	Linear Regression, Artificial Neural Network, Decision Tree, Support Vector Regression, Random Forest, AdaBoost, GBDT, XGBoost	The prediction of XGBoost is explained by SHAP	XGBoost is selected as the best model, in which the precision, recall, F1 score and accuracy of which are 97.30%, 94.74%, 96.00% and 99.02%, respectivel y.	[14]

Shasha Lu, Mohammadreza Koopialipoor , Panagiotis G. Asteris , Maziyar Bahri ,Danial Jahed Armaghani	A Novel Feature Selection Approach Based on Tree Models for Evaluating the Punching Shear Capacity of Steel Fiber-Reinforced Concrete Flat Slabs	Random forest , Random tree, and classification and regression trees (CART)	Novel feature selection (FS) technique has been used.	The range of R2 and RMSE values were obtained as 0.9476–0.9831 and 14.4965–24.9310, respectively; in this regard, could be applied to predicting SFRC flat slabs.	[15]
Duy-Thang Vu , Nhat-Duc Hoang	Punching shear capacity estimation of FRP-reinforced concrete slabs using a hybrid machine learning approach	Least squares support vector machine (LS-SVM)	Firefly algorithm (FA), a population-based metaheuristic, is utilised to facilitate the LS-SVM training.	New model has achieved roughly 55 and 15% reductions of Root Mean Squared Error compared with the Artificial Neural Network methods	[16]
Nhat-Duc Hoang	Estimating punching shear capacity of steel fibre reinforced concrete slabs using sequential piecewise multiple linear regression and artificial neural network	Piecewise multiple linear regression (PMLR)and Artificial neural network (ANN)	The algorithms of gradient descent and Levenberg-Marquardt backpropagation are employed to train the ANN.		[17]

Junho Song, Won-Hee Kang, Kang Su Kim, Sungmoon Jung	Probabilistic shear strength models for reinforced concrete beams without shear reinforcement	Probabilistic shear strength models	Using a Bayesian Method for parameter estimation.	Model predicts the result with improved accuracy and helps incorporate the model uncertainties into vulnerability estimations and risk-quantified designs.	[19]

3. MATERIAL AND DATASET

The flat slab system of reinforced concrete has been used more frequently because it has some advantages when compared to conventional structural systems[20]. Among these ad- vantages, one can mention greater architecture in defining internal environments or future layout changes; simplification of reinforcement and consequent reduction of labour and material costs; ease in the arrangement of installations and simplification of forms and framing[21]. The system also has disadvantages compared to conventional ones, such as higher levels of vertical displacement of the structure, reduction of the global stability and the possibility of failure by punching shear[22]. Punching shear is a type of shear failure that can occur in plate elements subjected to a concentrated load or reaction applied transversally and is characterized by occur- ring abruptly, which can lead the structure to ruin through progressive collapse[23]. The shear strength of the slab-Column connection is one of the most important parameters in the design of flat slab[24].
The original file is a database created by The American Concrete Institute Committee 445C with experimental results of 519 flat slabs tested by several authors since 1938. Experimental tests in Civil Engineering are usually performed with reduced size structures, due to the practical issues with testing real size structures. This is the cleaned data with fewer observations, since the goal is to predict punching shear resistance and some of the slabs in the original dataset did not fail by this mechanism[25].

Statistical Analysis and Data Distribution of various attributes in the dataset is as follows:-

	b1 (mm)	d1 (mm)	davg (mm)	ravg	b* (mm)	b*/davg	fc (MPa)	fy (MPa)	Pu (kN)
count	417.000000	22.000000	417.000000	417.000000	417.000000	417.000000	417.00000	417.000000	417.000000
mean	192.580336	378.636364	110.613691	0.011614	182.760224	1.853056	32.23763	461.633094	375.414868
std	105.556169	135.625375	64.160964	0.007330	94.425846	0.941617	17.95368	118.227971	436.956517
min	51.000000	152.000000	29.972000	0.000000	39.898227	0.306909	8.66200	250.000000	24.000000
25%	120.000000	275.250000	77.000000	0.007244	109.955743	1.200000	22.13500	359.000000	166.000000
50%	170.000000	360.000000	107.000000	0.010600	173.572994	1.735043	27.70000	462.000000	277.000000
75%	250.000000	480.000000	121.558210	0.014960	235.619449	2.222222	35.34000	530.000000	404.000000
max	901.000000	600.000000	668.500000	0.050105	707.643745	8.000000	118.70250	749.000000	4915.000000

Figure 1. Statistics analysis

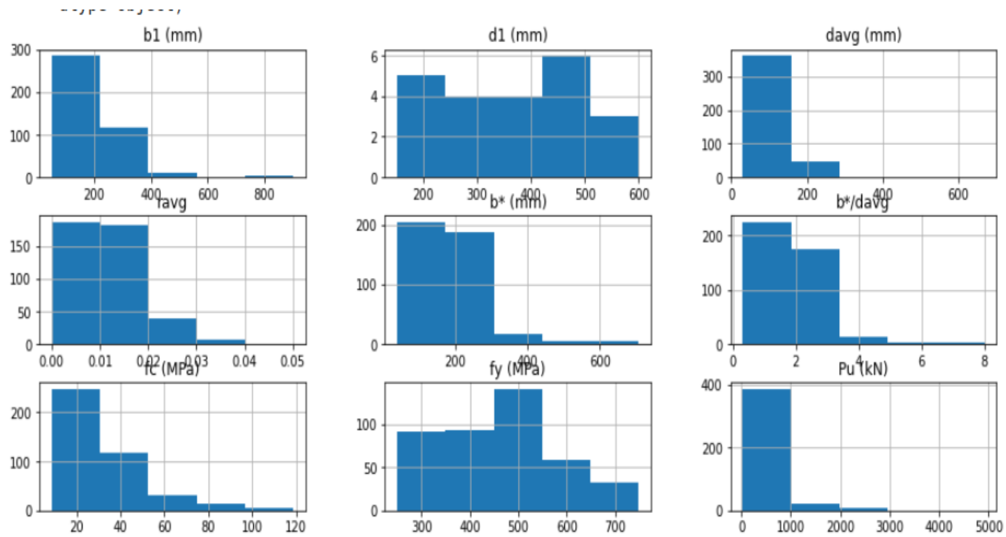

Figure 2. Data distribution of each feature

Dataset is being divided into 87.5 % for training purposes and 12.5 % for testing purposes. Features like Shape and d1(mm) are dropped because of its less significance and lots of null values. To analyze each shape's significance we converted it into numerical arrays using a one-hot encoding method. After the analysis of Heatmap of each variable, we observed that Shape S, C, R correlation with the target variable are significantly close to zero which indicates it is independent of the target variable. Therefore, the rest of the 7 features will be further processed to make a feature matrix. We have used MinMaxScaler() in Sklearn library which internally works as following:-

In which the minimum of features is made equal to zero and the maximum of features equal to one. MinMaxScaler() shrinks the data within the given range, usually of 0 to 1. It scales the values to a specific value range without changing the shape of the original distribution.

x_std = (x-x.min (axis=0)) / x.max(axis=0) – x.min (axis=0)) (3.1)

x_scaled = x_std* (max-min) + min (3.2)

Where,

- min, max = feature_range
- x.min (axis=0) : Minimum feature value
- x.max (axis=0) : Maximum feature value

#	Column	Non-Null Count	Dtype
0	Shape	417 non-null	object
1	b1 (mm)	417 non-null	int64
2	d1 (mm)	22 non-null	float64
3	davg (mm)	417 non-null	float64
4	ravg	417 non-null	float64
5	b* (mm)	417 non-null	float64
6	b*/davg	417 non-null	float64
7	fc (MPa)	417 non-null	float64
8	fy (MPa)	417 non-null	int64
9	Pu (kN)	417 non-null	int64

Figure 3. Null value table

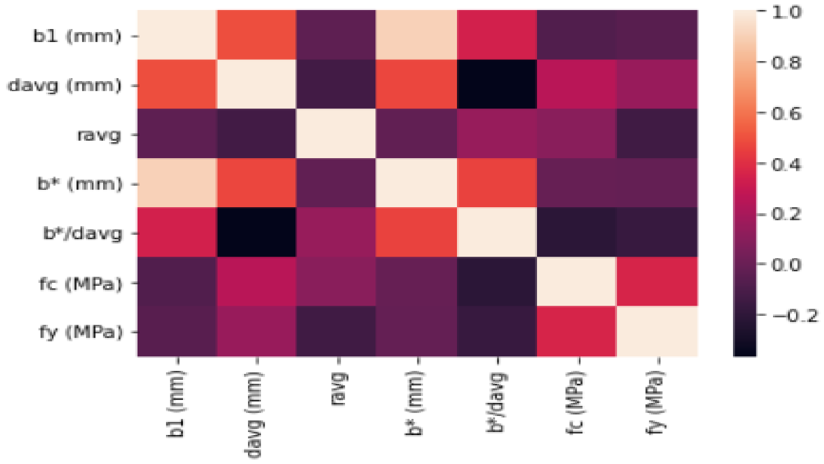

Figure 4. Heatmap

Shape
S
C
R

S	C	R
1	0	0
0	1	0
0	0	1

Figure 5. One hot encoding

	b1 (mm)	davg (mm)	ravg	b* (mm)	b*/davg	fc (MPa)	fy (MPa)
b1 (mm)	1.000000	0.495222	-0.031813	0.904989	0.347548	-0.076406	-0.057072
davg (mm)	0.495222	1.000000	-0.132432	0.474610	-0.368559	0.253327	0.152520
ravg	-0.031813	-0.132432	1.000000	-0.024454	0.146047	0.106222	-0.136264
b* (mm)	0.904989	0.474610	-0.024454	1.000000	0.464206	-0.009148	-0.011380
b*/davg	0.347548	-0.368559	0.146047	0.464206	1.000000	-0.212478	-0.168970
fc (MPa)	-0.076406	0.253327	0.106222	-0.009148	-0.212478	1.000000	0.363044
fy (MPa)	-0.057072	0.152520	-0.136264	-0.011380	-0.168970	0.363044	1.000000

Figure 6. Pearson correlation coefficient

4. METHODOLOGY

4.1. Introduction to Algorithms

4.1.1. Artificial Neural Network

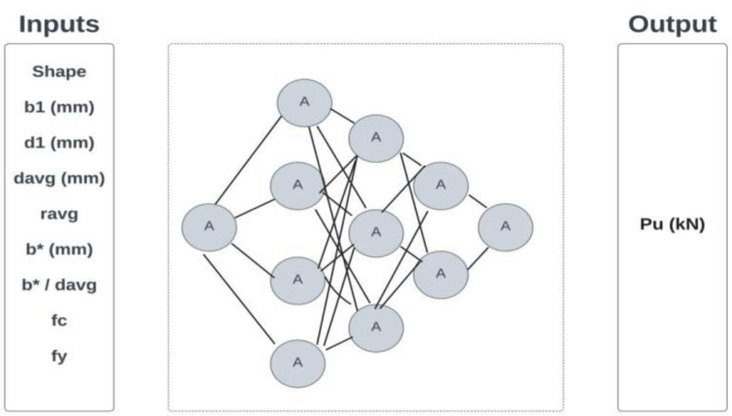

Figure 7. Artificial neural network

There's huge loss in terms of financial and materials because of current civil engineering methods. Failure during the construction phase of the project results in worker and staff fatalities. Punching shear strength becomes exceedingly boring, as was explained earlier while employing the old way. We can determine the shear strength by considering only a few in- puts, such as the column's shape, size, thickness of the slab, and compressive strength of the concrete, by employing machine learning.

There are a slew of traditional methods to evaluate the concrete's compressive and tensile strengths in order to see if it is strong enough to stand on its own. If not, determine whether the amount of reinforcement is fair, if not create rational things. Changing the structure comprises the following: increasing the slab's depth, modifying the slab's frame- work entails, increasing the slab's depth, increasing the slab's dimensions or by utilizing reinforcement that is both vertical and transverse.

Artificial neural network (ANN)[26] is a computing model whose layered structure resembles the networked structure of neurons in the brain [27] . It features interconnected processing elements called neurons that work together to produce an output function. Neural networks are made of input and output layer/dimensions, and in most cases, they also have a hidden layer consisting of units that transform the input into something that the output layer can use. Backpropagation algorithm [28] is used to train the neural network.

Input x**:** Set the corresponding activation a^1 for the input layer.
Feed forward: For each $l = 2, 3, \ldots$ L compute $z^1 = w^1 a^{l-1} + b^l$ and $a^l = \sigma(z^l)$. (4.1)
Output error δ^L**:** Compute the vector $\delta^L = \nabla_a C \odot \sigma'(z^l)$. (4.2)
Back propagate the error: For each l=L-1, L-2,…, 2 compute
$\delta^1 = ((w^{l+1})T \delta^{1+1}) \odot \sigma'(z^l)$. (4.3)
Output: The gradient of the cost function is given by

$$\frac{\partial c}{\partial_{w_{jk}^l}} = a_k^{l-1}\delta_j^l \frac{\partial c}{\partial_{w_{jk}^l}} = a_k^{l-1}\delta_j^l$$

and $$\frac{\partial c}{\partial b_j^l} = \partial_j^l \frac{\partial c}{\partial b_j^l} = \partial_j^l \quad (4.4)$$

4.1.2. Genetic Algorithm

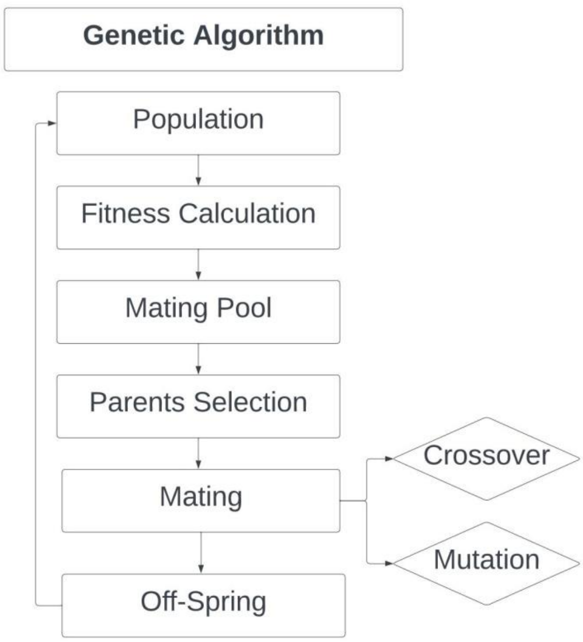

Figure 8. Genetic algorithm

The genetic algorithm [29] is a heuristic search and an optimization method inspired by the process of natural selection. It is widely used for finding a near-optimal solution to optimization problems with large parameter space. The evolution of species (solutions in our case) is mimicked by depending on biologically inspired components, e.g., crossover. Furthermore, as it does not take auxiliary information into account (e.g., derivatives), it can be used for discrete and continuous optimization.

For using a GA, two preconditions have to be fulfilled,

a) A solution representation or defining a chromosome
b) A fitness function[30]to evaluate produced solutions. In our case, a binary array is a genetic representation of a solution (see Figure 1) and the model's Root-Mean-Square Error (RMSE) on the validation set will act as a fitness value. Moreover, three basic operations that constitute a GA, are as follows:

1) Selection: It defines which solutions to preserve for further reproduction e.g. roulette wheel selection.
2) Crossover: It describes how new solutions are created from existing ones e.g. n-point crossover.
3) Mutation: Its aim is to introduce diversity and novelty into the solution pool by means of randomly swapping or turning-off solution bits e.g. binary mutation.

Occasionally, a technique called "Elitism" is also used, which preserves the few best solutions from the population and passes them on to the next generation [31]. Figure 8 depicts a complete genetic algorithm, where initial solutions (population) are randomly generated. Next, they are evaluated according to a fitness function, and selection, crossover, and mutation are performed afterward. This process is repeated for a defined number of iterations (called generations in GA terminology). In the end, a solution with the highest fitness score is selected as the best solution.

4.2. Model Architecture

ANN model consists of:

1) Input layer with one neuron

2) 3 Hidden layers with 8, 6, 6 neurons

3) Output layer with one neuron

4.3. Performance Evaluation

Throughout the experiments, Root Mean Square Error (RMSE) [32] is selected to judge the performance of the model. RMSE has 2 purposes:-

1) To serve as a heuristic for training models

2) To evaluate trained models for usefulness / accuracy RMSE is a good estimator [33] for the standard deviation of the distribution of our errors. Formula for RMSE is as follows:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}\left(y_{pred}^{(i)} - y^{(i)}\right)^2} \tag{4.3}$$

4.4. Training Approach

The training is used to assist the ANN in tuning its weights [34] in each layer to calculate a projected output that is as near to the training label as possible. To forecast the unknown data, GA was used to optimize the weights in each layer of the training model.

Initially, a fixed number of populations is specified. The weights of all levels in the sequential model are generated at random for each population.

The initial phase in the GA process is population initialization. It is a subset of solutions in current generations. There are two primary approaches for initialization of a Population in a GA:

1) Random Initialization [35]: totally random solutions are used to fill the initial population.
2) Heuristic Initialization [36]: fill the initial population using a problem-specific heuristic.

The training data will then be loaded into the training model, and the prediction process will begin. Following the fitness calculation, which indicates how fit or good the answer is in relation to the problem under discussion. Because it's weights are ideal, the programme will update the maximum fitness value for the final training stage, per- haps yielding better accuracy in the final training stage. This procedure will continue till the maximum generation is reached. The ideal matrix will be set to ANN model after optimizing the weight matrix and will be ready to generalize the testing data. The ANN model has one input layer, three hidden layers with 8,6,6 neurons, and one neuron in the output layer. By preventing the model from becoming locked in a local minimum situation, a Genetic algorithm might assist improve accuracy.

The GA [37] consists of three major components:

1) selection,
2) crossover, and
3) mutation.

First, the system picks the gene pool’s elite parents. The crossover is then implemented. Among the finest genes (weighted matrix), the process randomly picks two genes and recombines them in the following manner:

Select a random split point for the elite genes 1 and 2. Then join the second portion of gene 2 to the first part of gene 1, and repeat for the remaining parts of the two genes. As a result, I have two possible elite recombined genes. Third, because mutations occur at random, they are possible. After completing the crossover, the mechanism will create a random number between 0 and 1. If the randomly produced value is less than or equal to 0.05, a random section of the weighted matrix will be multi- plied by another random integer between 2 and 5. By gently scaling specific values in the weighted matrix, the mutation process can be aided in preventing the ANN model from being trained in the wrong direction.

Algorithm

```
SET Network=[]
SET Population to 20
FOR each Population
    CALL ANN()  // To define the architecture and set weighted matrix
   APPEND the Result in Network[]
SET Pool=[]
SET Optimal_Weight=[]
SET Generation to 0
SET Epoch to 30
FOR each Epoch
  Generation +=1
 FOR each ANN
    CALL ANN.Forward_Propoagtion()
    CALL ANN.Fitness_Score()
  APPEND the Results in Pool[]

 SORT(Pool) // According To Fitness Score

  FOR each Pool
      Compare with Max_Fitness and Update

  FOR each layer in ANN
       layer.get_weight()
       Append the Results in Optimal_Weight[]

  // Randomly Select Top 2 partners From 5 ANN
  Crossover(Pool[i], Random(Pool[i])) //To Create Child
  Mutation(child_weights) // To weighted matrix will be scaled up or down
```

Figure 9. Algorithm

5. EXPERIMENTS

5.1 Performance Evaluation of various Training Techniques

To examine alternative training algorithms or approaches, we evaluated ANN models with SGD (Stochastic Gradient Descent) [38], RMSprop (Root Mean Square Propagation) [39], and Adam (Adaptive Moment Estimation) [40] training methods. The outcomes of the various algorithms are shown below:

Table 2. Different optimizer and their corresponding RMSE score

Experimental observations	
Training Method	RMSE
Genetic Algorithm	0.192
SGD	0.216
RMSProp	0.176
Adam	0.160

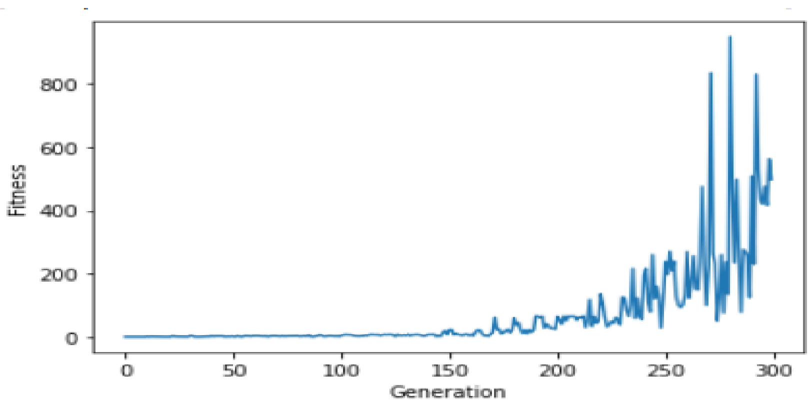

Figure 10. Fitness v/s generation

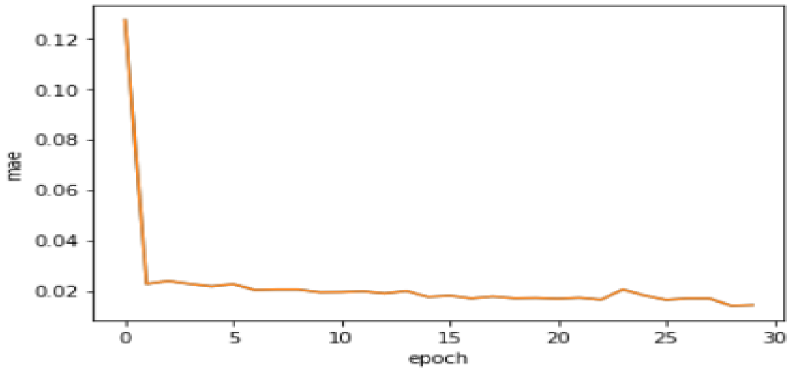

Figure 11. Sgd mae vs epoch

The experiment above shows that the stochastic gradient descent approach has a difficulty with convergence to the global minimum [41], resulting in lesser accuracy than alternative training methods. The genetic algorithm, on the other hand, works well because it includes selection, crossover, and mutation processes that may enhance the local minimum issue by developing various types of genes (weighted matrix) and picking the best among them.

There are several parameters that must be hyper-tuned [42], including:

1) Number of Neurons
2) Number of generations
3) Population size

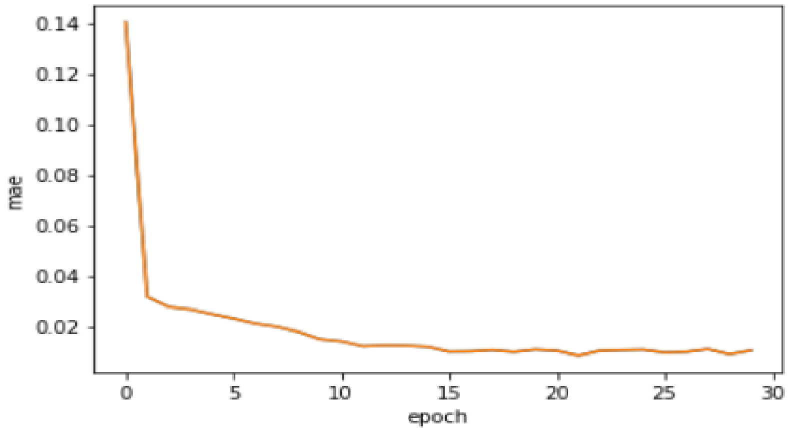

Figure 12. RMSprop mae vs epoch

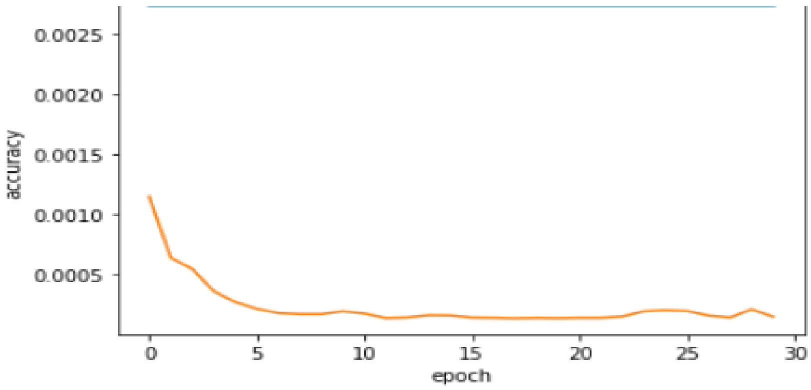

Figure 13. Adam epoch vs mae

1) We have increased the number of neurons by changing the architecture of the neural network defined in the code. We kept the number of layers constant.

We observed that the RMSE score lowers as the number of neurons grows, indicating that the model is improving.

Table 3. Number of neurons and their corresponding RMSE score

Experimental observations	
Neurons	RMSE
2	0.149
4	0.228
6	0.192
8	0.147
10	0.145

2) We have increased the number of generations used in the Genetic algorithm as a hyper-parameter. We increased the no. of generations by keeping other parameters constant.
We observed that there is no specific pattern as it first in- creases then decreases.

Table 4. Number of generations and their corresponding RMSE score

Experimental observations	
Generations	RMSE
10	0.181
25	0.195
50	0.184
100	0.318

3) We have increased the number of population used in Genetic algorithm as a hyper-parameter . We increased the no. of population by keeping other parameters constant.
We observed that there is no specific pattern as it first in- creases then decreases.

Table 5. Number of population and their corresponding RMSE score

Experimental observations	
Populations	RMSE
10	0.192
20	0.143
40	0.276
80	0.159
100	0.227

6. CONCLUSION

Civil engineering domain has emerged as one of the most significant industries all across the countries as it helps in the development of any nation. Infrastructure building by creating different means of transportation such as roadways, rail- ways, bridges, tunnels, telecommunication, schools, afford- able houses etc. is a significant barometer of any country's development.

There are a slew of ways in which punching pressure is calculated. Getting fully interpretable and unbiased results from these calculations is a really difficult task. A retrospective analytical building of models shows how to calculate the punching pressure using machine learning techniques such as ANN, genetic algorithms etc.

One major advantage of our machine learning approach is that it reduces the time period of calculations involved.
Generally in the civil engineering process, most of the calculations are done based on hypothesis and experiences which leads to biases and inaccuracies.

Apparently the machine learning model creates a function which takes required input and this leads to the reduction of the time. The Gradient Descent method [43] lays the foundation for machine learning and deep learning techniques.

The major fashion in which it has been used is a set number of populations initially specified. For each population, the weights for every level in the sequential model are created at random.
In this study, ANN, genetic algorithms, and other optimizers are used to determine the punch shear strength of reinforced concrete slabs.

The future efforts can be directed towards fine-tuning the neural network models using boosting methods such as gradient boosting. The experiments here used ANN models for primary training, but other types of deep learning models like CNN [44] and LSTM [45] can be used. Another possible approach is to fine-tune the other hyper-parameters used in algorithms like Mutation rate, scale value, split up point etc.

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LIST OF ABBREVIATIONS

ANN - Artificial neural network
EA - Evolutionary algorithms
SGD - Stochastic gradient descent
FRP - Fiber reinforced polymer
LR - Linear Regression
DT - Decision Tree
SVC - Support vector clustering
RF - Random Forest
GBDT - Gradient Boosting Decision Tree
XGBoost - eXtreme Gradient Boosting
SHAP - SHapley Additive exPlanations
random tree - (RT)
(CART) - classification and regression trees
firefly algorithm - (FA),
feature selection - (FS)
least squares support vector machine - (LS-SVM)
piecewise multiple linear regression - (PMLR)
sequential PMLR - (SPMLR)
MLR - Multiple Linear Regression
RMSE - Root-Mean-Square Error
R2 score - r squared score
RMSprop - Root Mean Square Propagation

Adam - Adaptive Moment Estimation
Mae - Mean absolute error
CNN - Convolutional neural network
LSTM - Long short-term memory

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