*Section A-Research paper*
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# Concrete Strength Prediction Model based on Bio-Inspired Honey Badger and Artificial Neural Network Algorithms

**Tushant Seth[1]*, Sandeep Singla[1]**

[1] *RIMT University, Mandi Gobindgarh, Punjab, India*

**Corresponding Author: tushantseth143@gmail.com*

**Abstract:** Based on the historical data, this research suggests a prediction model to calculate the strength of concrete. This study's main contribution is the reduction of the discrepancy between the concrete strength measurement model's projected value and actual value. In the suggested paradigm, artificial neural networks are used to do this. The effectiveness of the neural network depends on the weight values which connects the neurons in the network. However, determination of optimal weight value is difficult task. Therefore, bio-inspired honey badger algorithm is deployed for it. This algorithm based on the ingenious honey badger foraging techniques foraging behaviour of honey badger and provides better exploration rate to find the optimal solution based on the objective function over the algorithms. In the proposed model, the objective function used is the root mean square error and its value minimized to lessen the discrepancy between the projected and real value. The standard dataset is taken under consideration and various performance metrics such as Standard deviation of error (SDE), normalized mean absolute error (NMAE), mean absolute percent error (MAPE), and root mean square error and convergence rate are measured to validate the performance of the proposed prediction model. It is found that the proposed model achieves lower value of these performance metrics over the existing model based on ANN. Besides that, convergence rate graph shows that the honey badger algorithm is quickly determine the optimal weight values.

***Keywords:*** *Artificial Intelligence; Artificial Neural Network; Bio-Inspired Optimization; Concrete Strength Prediction; Honey Badger Algorithm; Machine Learning.*

## 1. Introduction

Concrete is sometimes considered the most commonly used building material because it offers many advantages over other materials, such as affordability, modularity, durability, and integrity. For the purpose of better understanding the behaviour of structures built of concrete under external loads and creating appropriate design techniques, it is vital to investigate the mechanical characteristics of concrete. The comprehensive strength is one of the fundamental components among various indices properties of concrete due to its direct link to the safety of the structures. During whole life cycle, compressive strength is required for determining the performance of the structures from old to new structural design and assessment. Cement pastes, extra combinations, coarse and fine particles, which are scattered at random throughout the concrete matrix, are some of the different components that make up concrete. Due to the current complex structure, it is difficult to estimate concrete's compressive strength precisely (Feng, D. C., & Li, J. 2016; Feng et al. 2016).

The physical experiments are generally used for obtaining the compressive strength of concrete. The cylindrical or cubic specimens were typically made for a certain planned mixture ratio and then cured for the necessary amount of time. Then, utilising a compressive test device, a compressive strength may be easily produced (Bischoff, P. H., & Perry, S. H. 1991; Lessard, M., Challal, O., & Aticin, P. C. 1993; Shi et al. 2009), but this is expensive in terms of both time and money, which reduces its working efficiency. Concrete compressive strength was estimated utilising suggested and some empirical regression techniques, which are distinct from the conventional experimental procedures, using the supplied intended mixing ratio (see (Bharatkumar et al. 2001; Bhanja, S., & Sengupta, B. 2002; FM Zain, M., & M Abd, S. 2009)). The accurate regression expression for that existing problem was difficult to derive due to the strongly nonlinear relationship shown for both compressive strength and concrete mixture. So, the concrete behaviour is captured using a third-way numerical simulation; see ((Feng et al. 2018; Feng et al. 2019). However, it is challenging to faithfully mimic the actual behaviour because randomness and nonlinearity are coupled (Feng, D. C., & Li, J. 2016; Feng et al. 2019).

To anticipate the compressive strength of concrete, machine learning (ML) methodologies are currently suggested given newly developed trends in artificial intelligence (AI). Machine learning (ML), a component of AI, may be used for many different purposes, such as classification, grouping, and regression. One utilization of the ML regression function is estimating the compressive strength of concrete. In contrast to traditional regression techniques, machine learning (ML) uses specific algorithms that are capable of learning from supplied data and produce very accurate answers for the output data (Salehi, H., & Burgueño, R. 2018; Feng et al. 2020).

Up to date, Multiple linear regression (FM Zain, M., & M Abd, S. 2009), K nearest neighbour (Beskopylny et al. 2022), adaptive neural fuzzy interference (Sharafati et al. 2021), and artificial neural network (Lee et al. 2003) are used for design concrete strength prediction model. Out of these algorithms, ANN is the most preferred algorithm because its ability to learn and model non-linear complex problem (Lee et al. 2003; Naderpour et al. 2018; Tabarsa et al. 2021; Moradi et al. 2021). In the ANN algorithm, neuron weight plays an important role which connects the neuron nodes. The optimal neuron weight values determination is a difficult task. Therefore, bio-inspired algorithms are deployed for it. The bio-inspired algorithm searches the solution space based on the objective function. The main aim of the bio-inspired algorithm is either minimize or maximize the objective for the given problem. In the literature, genetic algorithm is successfully applied for determine the optimal weight values of the ANN algorithm (Shariati et al. 2020). However, it faces low convergence rate due to selection and generation process of populations. Therefore, we have explored the other bio-inspired optimization algorithm that provides faster convergence rate and provides global solution. In comparison to other optimization algorithms, we have discovered that the honey badger algorithm offers higher rates of exploration and exploitation (Hashim et al. 2022).

The main contribution of this paper is to design a forecasting system that measures the concreate strength based on historical information. To achieve this goal, the ANN algorithm is taken under consideration. The weight values of it are determined using a bio-inspired honey badger algorithm. The honey badger's foraging strategy served as the inspiration for this algorithm. It provides better exploration and exploitation rates than the other optimization algorithms. It searches for the optimal weight values based on the objective function. In the method proposed, the objective function is minimized because the main objective is reduced to the discrepancy between the real and expected value. An objective function is defined as the root mean square error. Concrete strength prediction is done after determining optimal weight values. Next, simulation evaluation is performed on the standard dataset, which contains eight input and one output parameter. Based on these parameters, the ANN algorithm is trained and tested. Further, various performance metrics such as Root Mean Square Error (RMSE), Normalized Mean Absolute Error (NMAE), Mean Absolute Percentage Error (MAPE), and Standard Deviation of Error (SDE) are measured and compared with the existing model based on the ANN algorithm. The outcome demonstrates that the suggested approach yields an RMSE value of 11.779 over 90.348, a MAPE value of 39.818 over 363.65, a NMAE value of 0.70368 over 105.98, and a SDE value of 9.6372 over 87.457. Besides that, the convergence rate graph shows that the honey badger algorithm quickly determines the optimal weight values.

The remaining paper is defined into 6 sections. Section 2 demonstrates the related work in which an overview of ANN and bio-inspired honey badger algorithm. Section 3 explains the proposed concrete strength prediction model. Section 4 shows the simulation evaluation. In the last, conclusion and future trends is shown in Section 5.

## 2. Related Work

In this section, an overview of ANN and bio inspired honey badger algorithm is given to understand the proposed method.

### 2.1 Artificial Neural Network

Artificial neurons make up a nonlinear information processing network called an artificial neural network (ANN), which mimics biological learning behaviour. Since the model is data-driven, it may discover the nonlinear interactions at play in the process (Akbari, M., & Jafari Deligani, V. 2020).
One neural network topology that is widely used in engineering applications is the multi-layer feedforward neural network. In addition to a number of layers of neurons or nodes, it also contains one or more hidden layers, an input layer, and an output layer. The weighted inputs are obtained from other neurons using the activation function, which then communicates its output to other neurons.

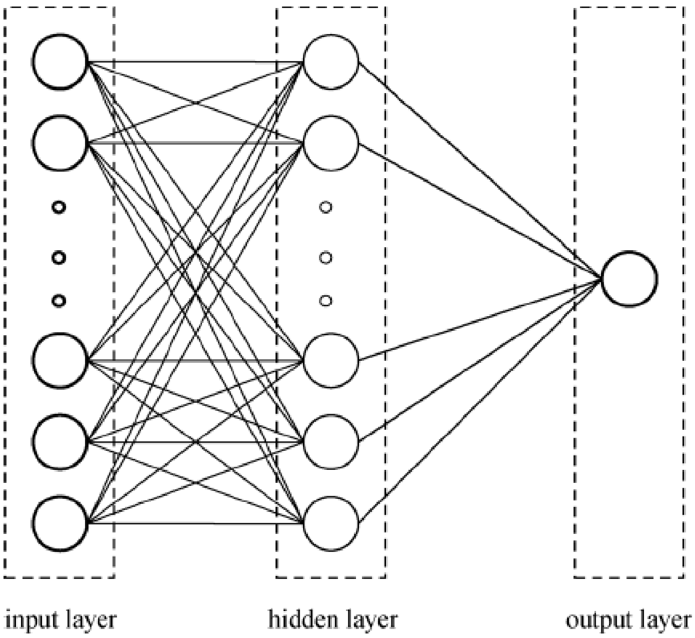


Figure 1 Multi-layer Feed-Forward Neural Network (Akbari, M., & Jafari Deligani, V. 2020)

According to research by (Hornik et al. 1989), The number of neurons in a network with only one hidden units is sufficient to estimate a function with the required precision. They employed a single hidden layer network as a result in several distinct investigations. Figure 1 is a schematic representation of a multi-layer feed-forward neural network (Akbari, M., & Afshar, A. 2014). The equation used for calculation is given below in Eq. (1).

$$\hat{y} = f\left(\sum_{j=1}^{q} w_j^i g\left(\sum_{i=1}^{m} x_i w_{ij} + b_j\right) + b'\right) \quad (1)$$

In the equation above, f stands for the transfer functions for output and g for hidden layers, $w_{ij}$ for input to hidden and $w'_j$ for hidden to output layers, $b_j$ for hidden and b' for output layers, and q for the number of neurons in the hidden layer.

The number of hidden layer neurons for each ANN model was calculated through a process of trial and error. In order to construct models, different hidden neuron count network layouts are put to the test to determine which design of the network is most accurate. Network training means the weights and biases adjustment of the networks done to matches the out of ANN with measured output. Due to this, the bio-inspired optimization algorithm and proposed method were taken into consideration for determining the optimal parameter values of ANN algorithm.

## 2.2 Honey Badger Algorithm (HBA)

The majority of this mammal's habitats are semi-desert and rainforests in the Indian subcontinent, Africa, and Southwest Asia. It has fluffy black and white fur (Hashim et al. 2022). It is renowned for its fearlessness. HBA copies that foraging behaviour of honey badger and they either dig or follows honeyguide bird for locating their source of food. The first case is known as digging model and other one is honey mode. In the first mode, they use their smelling talent for approximating the location of prey and then it moves around the prey after they reach for selecting the appropriate place for catching and digging the prey. When searching for hives directly in later modes, the honey badger uses the honey guide's bird advice. As mentioned in the above section, HBA is broken down into the digging and honey phases that is explained in details in the below text.

• Algorithmic procedures

This section presents the formulas for the proposed HBA algorithm. In theoretical terms, HBA algorithm is made up of two phases namely exploration and exploitation that make it to refer as global optimization algorithm. The Algorithm 1 presents a pseudo-code of the proposed algorithm that consists of evaluation, population initialization and updating of parameters. The mathematical steps are given in detailed as the following. Below equation is used for representing the HBA population of candidate solutions:

$$\text{Population of candidate solutions} = \begin{bmatrix} x_{11} & x_{12} & x_{13} & \dots & x_{1D} \\ x_{21} & x_{22} & x_{23} & \dots & x_{2D} \\ & & \dots\dots\dots\dots & & \\ x_{n1} & x_{n2} & x_{n3} & \dots & x_{nD} \end{bmatrix}$$

$$i\text{th position of honey badger } x_i = \left[x_i^1, x_i^2, \dots, x_i^D\right]$$

Step 1: Initialization phase: Using Eq (2), the number of honey badgers for a population of size N is initialised, along with each animal's location.

$$x_i = lb_i + r_1 \times (ub_i - lb_i), r_1 \in (0,1) \ (2)$$

Xi is used to denote the I$^{th}$ honey badger position, which refers to a potential solution in a N population; $lb_i$ and $ub_i$ are the low and upper limits of the search area, respectively.

Step 2: Defining intensity (I): The density of prey and the distance between it and the honey badger were determined by intensity. Small intensity of the prey is defined by $I_i$, and motion become fast by high smell, vice and versa that is given using Inverse square law [35] and defined by Eq. (3).

$$I_i = r_2 \times \frac{S}{4\pi d_i^2} r_2 \in (0,1) \ (3)$$

$$S = (x_i - x_{i+1})^2$$

$$d_i = x_{prey} - x_i$$

Where, the source or concentration strength is defined by S for prey location shown in figure 2, $d_i$ in Eq. (3) is denote the Prey's distance from the i$^{th}$ badger.

Step 3: Revise the density factor: A smooth transition from exploration to exploitation is made possible by the density factor (α), which controls time-varying unpredictability. To lessen unpredictability, update the decreasing factor, which gets smaller with time, using Eq. (4).

$$\alpha = C \times \exp\left(\frac{-t}{t_{max}}\right) \ (4)$$

In eq. (4), $t_{max}$ denotes the maximum number of iterations, whereas C is a constant and its default value is 2.

Step 4: Breaking out of the local optimum: The next two methods are used to break away from local optimal areas after escaping from the local optimum. In order to provide high possibilities for agents to scan the search space, flag F was employed in the suggested method to change search direction.

Step 5: Position updates for the agents: The $x_{new}$ is the HBA position, which is further separated into the phase of digging and the phase of honey. The explanation for these two phases is provided in the section below.

Step 5-1: Digging phase: In this phase of HAD, a similar action to Cardioid shape is performs by honey badger [2]. This action is shown in Figure 3 and it can be simulated using Eq. (5).

$$x_{new} = x_{prey} + F \times \beta \times I \times x_{prey} + F \times r_3 \times \alpha \times d_i \times |\cos(2\pi r_4) \times [1 - \cos(2\pi r_5)]| \quad (5)$$

In the above Eq. (5), $x_{prey}$ denotes the best position so far of the prey that can be known as global best position. $\beta \geq 1$ (default = 6) is the ability of honey badger in getting food and $d_i$ denotes the distance between prey and $i^{th}$ honey badger given in Eq. (3). Three different random numbers are $r_3$, $r_4$ and $r_5$ and its value is varying between o and 1. F serves as a flag altering the direction of search and can be measured using Eq. (6):

$$F = \begin{cases} 1 \ if \ r_6 \leq 0.5 \\ -1 \ else \ \ r_6 \in (0,1) \end{cases} (6)$$

In this phase, honey badger is depending on smell intensity I of prey $x_{prey}$, $\alpha$ a time-varying search influence factor and distance between the prey di and badger. Moreover, during digging, any disturbance F can be received by badger that allows it for finding better location for prey.

Step 5-2: Honey phase: The below given Eq. (7) is used by honey badger to reach beehive by following the honey guide bird.

$$x_{new} = x_{prey} + F \times r_7 \times \alpha \times d_i, r_7 \in (0,1)$$

In the above equation, $x_{new}$ is refer as latest position of honey badger, prey location is denoted by $x_{prey}$, F is determined using Eq. (6) and Eq. (4) is used to determine $\alpha$. The Eq. (7) shows that search close to prey location $x_{prey}$ is perform by honey badger by considering distant details. At this stage, the search is mainly influenced by the behaviour of the search based on time $\alpha$ and disturbance F can be found by Honey badger.

**3. Proposed Concrete Strength Prediction Model**

This section explains the proposed concrete strength prediction model is based on the bio-inspired honey badger and ANN. In the proposed model, ANN algorithm is used for prediction purposes and optimal weight value of ANN algorithm is determined using bio-inspired honey badger algorithm. The flowchart of the proposed model for concrete strength prediction is shown in Figure 2.

Initially, standard database is read. The database is available in the .xls format. The database contains 8 input parameters such as *blast furnace slag*, *cement*, *fly ash*, *superplasticizer*, *water*, *coarse aggregate*, *fine aggregate age* and one output parameter known as *concreate compressive strength.* The pre-processing of the database is done to fill the empty or missing parameter value and to split the database into input and output parameter value. Next, ANN algorithm is trained. Further, get weight value of ANN and optimized its value using bio-inspired honey badger algorithm. Next, concrete strength prediction is done using the ANN algorithm. Finally, Mean Absolute Percentage Error (MAPE), Normalized Mean Absolute Error (NMAE), Root Mean Square Error (RMSE), Standard Deviation of Error (SDE), and Convergence Rate are used to analyse the performance of the suggested technique.

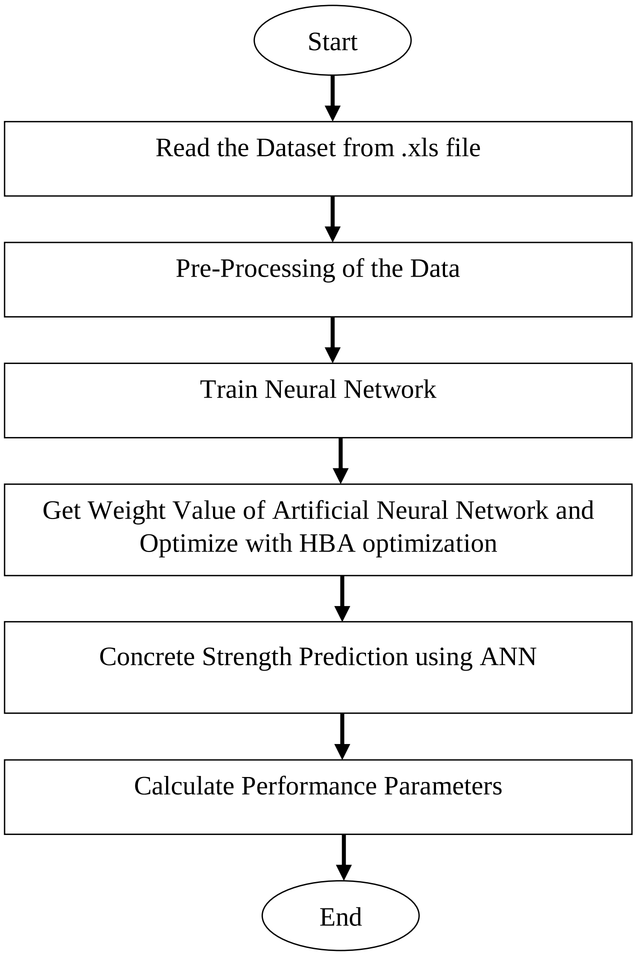



Figure 2 Proposed Model for Concrete Strength Prediction

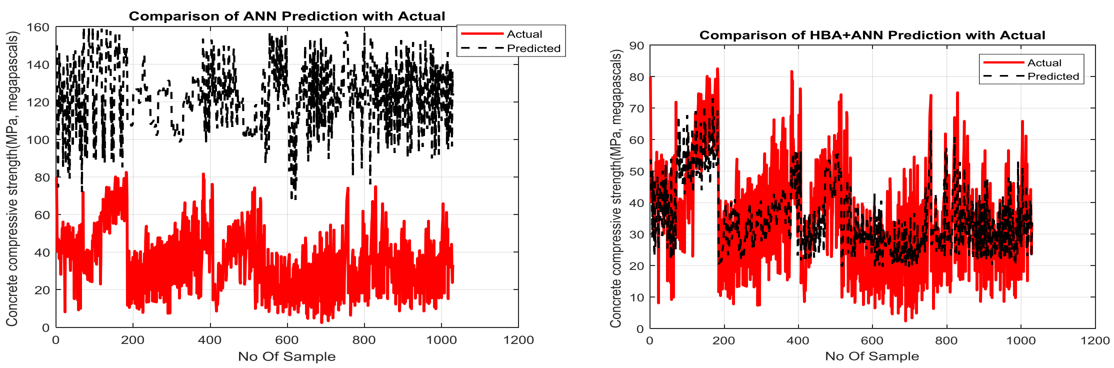
## 4. Simulation Evaluation

This section shows the simulation evaluation is performed for the proposed model to evaluate its performance over the existing models. The standard database of concreate is taken under consideration. MATLAB software is used for simulation purposes. Table 1 shows the ANN and bio-inspired honey badger algorithm parameter values.

Table 1 Parameter Values of the ANN and Bio-Inspired Honey Badger Algorithm

| Parameter | Value |
|---|---|
| Total Population | 10 |
| Iterations | 100 |
| Beta | 6 |
| C | 2 |
| ANN Network | Feed Forward |

Figure 3 shows the graph plotted between no. of samples vs. concreate compressive strength for actual and predicted value for ANN and proposed model based on HBA-ANN algorithm. The result shows that the proposed model prediction is superior over the ANN algorithm.




(a) ANN (b) Proposed Model based on HBA-ANN Algorithm

Figure 3 No. of Samples vs. Concrete Compressive Strength for ANN Algorithm (a) and Proposed Model based on Bio-inspired HBA-ANN algorithm (b)

Figure 4 shows the convergence rate graph plotted between iterations vs. objective function. The result shows that the honey badger algorithm quickly search the optimal solution.

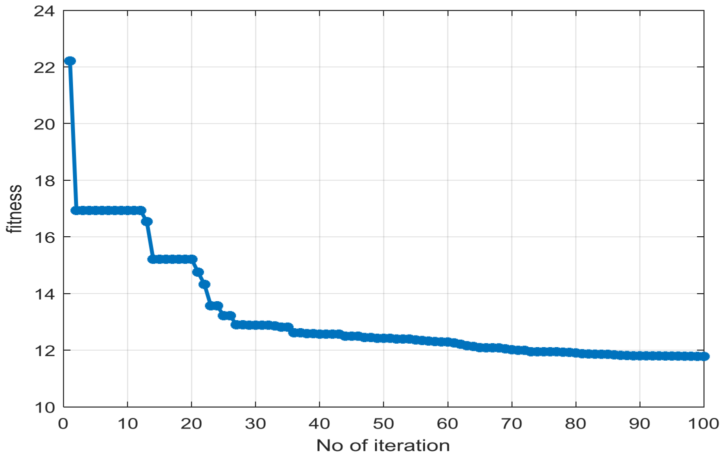



Figure 4 Convergence Rate (Iterations vs. Objective Function)

Further, four parameters are used to evaluate the performance of the proposed model, as shown in Table 2.

Table 2 Performance Parameters

| Parameter | Equation |
|---|---|
| Root Mean Square Error (RMSE) | $RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(O_i - P_i)^2}$ |
| Mean Absolute Percentage Error (MAPE) | $MAPE = \frac{100}{N}\sum_{i=1}^{N}\lvert\frac{O_i - P_i}{O_i}\rvert$ |
| Normalized Mean Absolute Error (NMAE) | $NMAE = \frac{1}{N}\sum_{i=1}^{N}\lvert\frac{O_i - P_i}{O_{Peak}}\rvert$ |
| Standard Deviation of Error (SDE) | $SDE = \frac{1}{N}\sum_{i=1}^{N} e_p - \overline{e}$ |

Note: In RMSE, MAPE, and NMAE parameter, O denotes the original and P denotes the predicted value. On the other hand, in SDE parameter, $e_p$ predicted error whereas $\overline{e}$ is the mean error value.

Table 3 shows the comparative analysis of the proposed model with the existing ANN based on various parameters. Figure 5(a-d) shows that the suggested model succeeds in lower parameter values over the existing model based on ANN algorithm.

Table 3 Comparative Analysis based on Various Parameters

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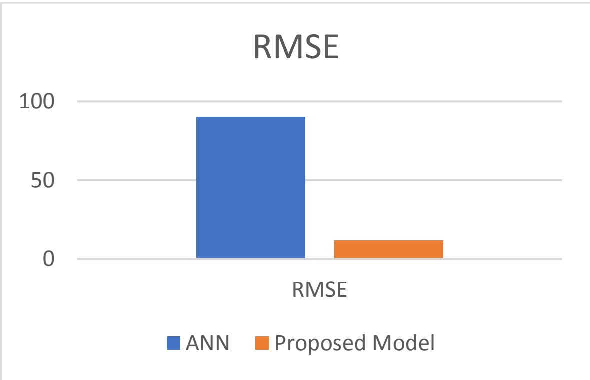
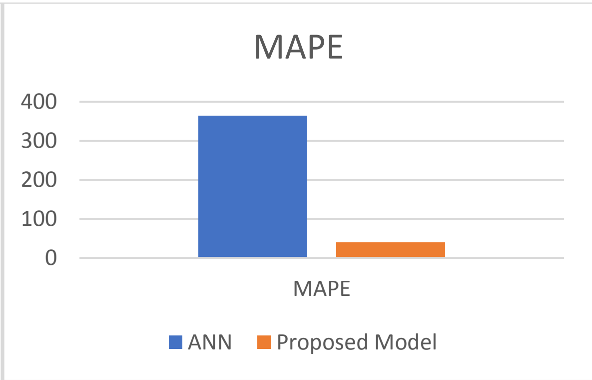
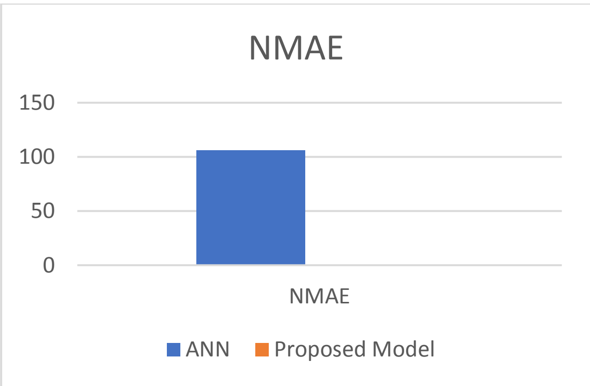
| Parameter | ANN | Proposed Model |
|---|---|---|
| RMSE | 90.348 | 11.779 |
| MAPE | 363.65 | 39.818 |
| NMAE | 105.98 | 0.70368 |
| SDE | 87.457 | 9.6372 |



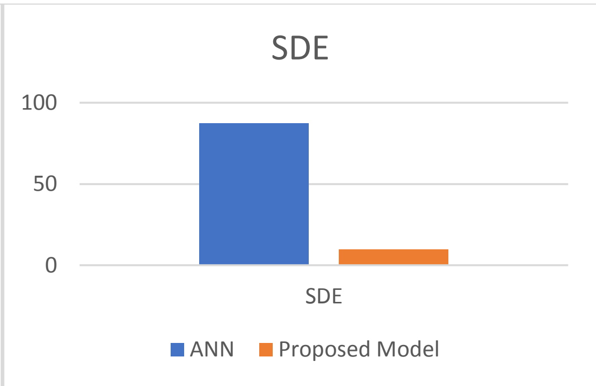

(a)




(b)




(c)




(d)

Figure 5 Comparative Analysis (a-d)

## 5. Conclusion and Future Trends

In this paper, we've created a concrete strength prediction model using ANN. Further, the optimal weight of the ANN algorithm is resolved using the bio-inspired honey badger algorithm. In the bio-inspired algorithm, root mean square error (RMSE) is taken as objective function to determine the optimal weight and its value is minimized in the proposed model. The simulation evaluation is done on the standard dataset which is downloaded from Kaggle. The simulation is performed in MATLAB software and various performance metrics such as

Standard deviation of error (SDE), Normalized Mean Absolute Error (NMAE), Mean Absolute Percentage Error (MAPE), and Root Mean Square Error (RMSE) are calculated for the proposed model and compared to the current ANN model. The findings demonstrate that, compared to the ANN model, the suggested technique produces lower values for these parameters.

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