Efficient Prediction of Bridge Conditions Using Modified Convolutional Neural Network

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Abstract
Artificial Intelligence (AI) technology has proved itself as a proficient substitute for classical techniques of modeling. AI is a branch of computer science with the help of which machines and software with intelligence similar to humans can be developed. Many problems related to structural as well as civil engineering are exaggerated with uncertainties that are difficult to be solved using traditional techniques. AI proves advantageous in solving these complex problems. Presently, a comprehensive model based on the convolutional neural network technique of artificial intelligence is developed. This model is advantageous in accurately predicting the structure of a bridge without the need for actual testing. The firefly algorithm is used as a technique for accurate feature selection. The database is taken from national bridge inventory (NBI) using internet sources. Different performance measures like accuracy, recall, precision, and F1 score are considered for accurate prediction of the bridge structure and also provide advantages in actual monitoring and controlling of bridges. The proposed CNN model is used to measure these parameters and to provide a comparison with the standard CNN model. The proposed model provides a considerable amount of accuracy (97.49%) as compared to accuracy value (85%) using the standard CNN model.

Keywords Bridge conditions · Artificial intelligence · Convolutional neural network (CNN) · Firefly algorithm · Optimization · Health monitoring of structures
1 Introduction

Bridges act as an essential source for mass expansion or departure or even as supply chain operations at the time of disasters, and they also act as important communications that provide commuters, a prime means for ground transportation. Over the last few decades, bridges are constructed to undergo mass loading circumstances as per their planned significance [1]. Bridges are designed to endure increased demand of population on a continuous basis, unique high load traits as well as ruthless weather conditions like rainfall, snowfall, etc. for a long lifetime. Different circumstances like tsunamis, wildfires, floods can be caused due to climatic change or natural calamities like landslides, earthquakes and also situations made by humans due to accidental errors like vehicle crash, tanker force etc. to those like a terror attack, fire-raising etc. that occur with intent to harm should be withstood by bridges [2, 3]. Briefly, the faster damaging and shortening of the life span of bridges is quite attributable to fast urbanization leading to high vehicular and load density that these bridges have to bear in the present day. Moreover, the location and accessibility to the public for use in rapid travel and logistics requirements not much can be done about their security [4, 5]. It is for such reasons that the majority of bridges is ill-maintained or cannot be easily well maintained, and they are fast deteriorating [6]. Recent studies have also shown that such factors as enumerated above combined with other unfavorable geographical or geo-climatic circumstances lead to faster depreciation or damage to the bridges [7, 8]. The combination of previously enumerated factors has often led to increasing cases of bridge failures/collapse in the last decade. [9–11]. Despite technological improvements in design and materials such as usage of high strength alloys, high performance concretes, updated bridge design codes, and standards in place, these bridges continue to fail. Upon close scrutiny, it has been learned that a majority of these serviceable bridges failed due to direct exposure to an event causing extreme stresses such as storm, fire, or during scour etc. [12]. Although while quite some work has been done to develop and enhance the efficacy of the bridges in terms of knowledge and materials to cater to the load-bearing capacities, vehicular density and impact of disasters like storms, earthquakes [13–15]; yet there is lack of fire safety measures [1, 8, 13] that lead to the bridge failures.

There are several complexities in the field of structural engineering such as design, analysis, condition monitoring, building management, decision-making, etc. Such problems require equations in mathematics, physics and dynamics, and their method depends largely on the observations of professionals. It can also be stated because certain functions already do not have full computers. This is mainly due to the use of logical rationale; issues tend to be specific, drawbacks of their viability and the need to allow use of expertise in design and analysis [16]. The AI technology therefore, may be used successfully to improve these attempts and the overall validity of research lab or field test findings may also be regarded. AI methods can also reduce time usage through research lab or tests conducted to mitigate (and potentially avoid) design parameters. Safety is an inherent aspect of the challenges of structural engineering. For starters, earthquake specifications are not accurately known in seismic design [17]. One of the major AI subfields is Machine learning, which deals with the design, development, and study of algorithms. In ML data can be learned for making predictions using this learned data [18, 19]. ML is referred as the ability of computers of learning without any explicit programming. Machine learning models are of two types: predictive and descriptive, both are used to attain the data knowledge [20, 21]. ML has also been used for effective prediction of structural conditions and health monitoring of concrete structures [22, 23]. The potential and scope of ML is more generalized as compared
to other AI techniques and find scopes in disciplines like: information theory, computer science, statistics and probability, computational complexity, theory and philosophy, and financial market [24, 25]. It is important to discriminate ML among other AI subsets like deep learning (DL) and pattern recognition (PR). Generally, ML and PR are closely associated with each other, as their scope is fundamentally same. Though, PR deals with classification methods, while ML is based on algorithms used for learning.

In this work, a firefly algorithm is used for feature extraction followed by Convolutional neural network for predicting the bridge using performance parameters like accuracy, precision, recall, and F1 score.

2 Firefly Algorithm

Many nature-inspired algorithms were presented as powerful ways to solving continuous optimization issues in recent years, and many of these algorithms have been implemented in practice. An optimization problem is one in which the number of variables is minimized while the accuracy of forecasting is maximized [26]. The firefly algorithm (FA) is one of the newly efficient suggested nature-inspired algorithms, which was presented by Yang [27]. FA is one of the newly effective recommended nature inspired algorithms. When compared to other optimization techniques, the use of FA is a straightforward approach for addressing optimization issues. FA is influenced by the cultural behaviour of fireflies and is characterized by the use of lights. FA allows a swarm of flies with low intensities to travel towards the brighter neighbouring fireflies with greater search skills in order to solve optimization difficulties [28, 29]. In non-linear situations, the firefly method has the capability of determining optimal values (e.g. scour depth). When compared to other optimization approaches, this method offers a more accurate search process [27]. Its rapid convergence rate results in a reduction in computing volume while also allowing it to achieve a convergent answer in a relatively short number of rounds. When using this approach, the target function is merely adjusted to account for the brightness of the firefly in the environment. Fireflies utilize light signals to capture the attention of other fireflies in search of partners. Yang created a meta-heuristic algorithm that was based on the behavior of the subject. All of the fireflies are regarded to be unisexual, and the brightness of their flash is directly related to their ability to attract a mate. Consequently, when given the option of going toward either of two different fireflies, a firefly particle will be more tempted to the firefly with greater brightness and will migrate in that way. When there are no fireflies in the immediate vicinity, the firefly will move in an unpredictable manner. There are three rules that govern the firefly algorithm, and they are as follows:

1. No matter what their gender, fireflies are drawn to one other.
2. Because their brightness diminishes with distance, their attractiveness is directly related to how attractive they are to others.
3. The objective function environment influences a firefly’s brightness

This algorithm is also termed a stochastic meta-heuristic algorithm. For this reason, the algorithm may generate a large number of potential solutions.

By putting a flashing light in front of the objective function, we are able to see how well the algorithm is doing as a whole. The biochemically induced flashing light of fireflies
distinguishes them. This algorithm was designed on the basis of based behavior and flashing patterns of fireflies. In reality, the following three ideal rules are used by FA:

- Fireflies are mostly unisex in nature; so, the attraction between different fireflies will be present regardless of the sex of fireflies.
- The attractiveness and brightness are directly proportional with each other but are inversely proportional with distance. Thus, the value of both parameters is decreased with increasing the distance. So, in a case where any two fireflies are flashing, less bright firefly will get attracted towards a brighter firefly. Also, if a particular firefly is brightest of all, then its movement will be random.
- A firefly’s brightness can be established by an objective function. Firefly attractiveness directly depends on light intensity perceived by neighbouring fireflies, variation in attractiveness (β) can be defined with respect to distance (r), and is provided by relationships in Eq. 1 as:

\[ \beta = \beta_0 e^{-r^2} \]  

(1)

here \( \beta_0 \) is the value of attractiveness at distance \( r=0 \). A particular firefly’s movement towards a brighter firefly ‘\( j \)’ can be determined by Eq. 2 as:

\[ x^{t+1}_i = x^t_i + \beta_0 e^{-r^2} j \left( x^t_j - x^t_i \right) + \alpha_i \epsilon^t_i \]  

(2)

In Eq. 2, second term is because of attraction. Last term is because of randomization and \( \alpha_i \) is the randomization parameter, also \( \epsilon_i^t \) is a vector with all the numbers as random which is drawn using Gaussian distribution function at any time (t).

The case with \( \beta_0=0 \) is considered as a random walk. Additionally, the randomization parameter \( \alpha_i \) can be expanded to other distribution functions like L’evy flight function [30].

Different steps for feature evaluation using Firefly Algorithm for Feature Extraction (FAFS) are:

Step 1: Generation of an initial population
An initial population of fireflies is generated in this step. Each firefly is considered as a new subset with different features.

Step 2: Evaluation of initial position
Each position is evaluated as per different classifiers for detecting the reduction rate and accuracy of the subset with different features. Here, the fitness function is calculated for each firefly.

Step 3: Movement towards brighter
In this step, the fitness of each firefly is compared with other fireflies and the movement of less bright firefly is noticed towards firefly with more brightness. For this movement, parameters like distance (\( r \)) and attractiveness (\( A \)) are used.

Step 4: Evaluation of new position
A new position is evaluated as per different classifiers for detecting the reduction rate and accuracy rate of the subset with different features. The fitness function of every new firefly is again calculated. Equations 3, 4 and 5 are used to calculate fitness function:

\[ S_x = \sqrt{\left( \frac{1}{n-1} \sum_{i=1}^{n} (x_i - \bar{x})^2 \right)} \]  

(3)
where \( \bar{x} = \frac{1}{n} \sum_{i=1}^{n} x_i \)  

Fitness = \( \frac{1}{n} \sum_{i=1}^{n} S_x(X) \)  

Here \( S_x \) is Standard deviation, \( \bar{x} \) is mean of data and \( X \) is represent of data.

**Step 5: Ranking and Updating**

Here, all fireflies are ranked as per the fitness function for selecting a subset with best position. The subset that contains the best features is updated. The algorithm is stopped when best feature subset is selected and stopping criteria is met, otherwise step 3 is repeated.

The pseudo code for firefly algorithm is given below:

| PSEUDO CODE FOR FIREFLY ALGORITHM |
|-----------------------------------|
| **begin** |
| Objective function \( f(x) \), \( x = (x_1, x_2, ..., x_d) \) where ‘x’ is a ‘d’ dimensional input parameter |
| Generate initial population of fireflies with population size ‘n’ i.e. \( x_i \) (\( i = 1, 2, 3, ..., n \)). |
| Define light absorption coefficient ‘\( \gamma \)’. |
| **While** (termination criteria is not met) |
| **for** \( i = 1: n \) |
| **for** \( j = 1: n \) |
| **if** \( \beta_j > \beta_i \) |
| Move firefly \( j \) towards firefly \( i \) |
| **end if** |
| Attractiveness varies with distance via Eq.(1) |
| Evaluate new solutions using Eq.(2) and update attractiveness |
| Light intensity or attractiveness is determined by fitness function using Eq. (3)-(5) |
| **end for** \( j \) |
| **end for** \( i \) |
| Rank the fireflies and find the current best |
| **end while** |
| best firefly is selected as the optimal solution of the problem |
| **end** |

### 3 Convolutional Neural Network (CNN)

CNN is a branch of artificial networks that is rising today in leaps and bounds and attracting the interest of a lot of researchers [18]. It can adapt and learn 3D features of back propagation automatically. It consists of numerous building blocks like convolution layer, ReLu layer, pooling layer, fully connected layer etc. as shown in Fig. 1.

The detailed description of the CNN layers explained below [31].
**Input Layer** To specify the input database size, we can use the different input layer sizes according to the input training database. NBI database have 1595 rows and 136 columns. We have used in proposed work 1595 rows and 10 columns for training.

**Convolution Layer** In this layer, the filter size argument is the size of the filter and thickness. This function is used to scan images where number size 3 indicates that filter size is 3-by-3. The next argument specifies the filter numbers (num Filter). This argument is used to specify how many neurons are connected to the same input. Another vital feature is padding, and in the feature map, if the default padding size is 1, it assures that the output is the same as the input.

**Batch Normalized Layer** Batch normalization is followed by an activation function that is non-linear. Usually, the activation function is the rectified layer unit (ReLu).

**ReLu Layer** In this layer, if any gradients actively propagate through networks are normalized. Thus, it helps the training network an easy optimization problem. This layer is used between the convolution layer and non-linearities such as ReLu help to process up or making it fast for network training and reduce sensitivity.

**Max Pooling layer** All the duplicity or copied information is removed by using Convolution layers; a down-sampling operation is then followed for size minimization. We can raise the number of filters in the convolution layer without any complex calculation by using Down-sampling. Down-sampling uses max pooling; this is created by using the max Pooling Layer.

**Fully Connected Layer** After the convolution layer, there comes the down-sampling layer and then a fully connected layer where every neuron is connected to all the neurons present in previous layer. This layer also mixes all the features learned in previous layers for detecting large pattern images. Here the Output size Parameter is similar to different classes in the target data.

**Dropout Layer** This layer arbitrarily gives input elements value to zero with a given probability. I set 0.2, where 0 shown by drop-out mask random (size(X)) < Probability, where layer input X is scaled with the leftover elements by 1/(1-probability). This is how I change network architecture with repetitions and, thus, prevent the network from over-fitting.

**Regression Output Layer** For the regression problem, I have to find out the half-mean-squared-error loss. For distinctive relapse in one observation, the mean squared error is given by Eq. (6).

\[
MSE = \frac{1}{R} \sum_{i=1}^{K} \frac{(t_i - y_i)^2}{R}
\]  

(6)

where R indicates responses, target output, and Y network’s prediction for the response.

**4 Proposed Method**

In order to monitor the bridge conditions, a Convolution Neural Network (CNN) based prediction model has been designed.

In the proposed method, the National Bridge Inventory (NBI) database has been used for rating a bridge condition based on deep learning. The present research aims at developing a data-driven method that enables predicting the future conditions for components of a highway bridge from inspection data. To solve the problem, a Convolutional Neural Network (CNN) model is trained with NBI data available online. We proposed a firefly optimization
based feature selection and Convolutional Neural Network (CNN) model-based classification. Feature Selection (termed as attribute selection) is a process of automatic searching the best attributes subset from the dataset available online. The notion “best” relates to a problem that need to be solved but usually means the maximum accuracy. A useful method of thinking about a problem and selecting its attributes using a search space: search space is distinct and is consisting of attributes with all feasible combinations that can be chosen from the available dataset. The aim is navigating through a search space, locating the best combination that can improve the performance after selecting all the attributes. The feature selection approach can help to improve the CNN model performance and provide advantages like less redundancy in data means less chance of making noise-based decisions, fewer data misleading to improve model accuracy, and algorithms will train faster.

4.1 Methodology

In this section, we have explained the different components used in the flowchart. The flowchart for the proposed technique is as provide by Fig. 2.

1. The first step is to extract dataset information from an excel file for further process. We have used the National Bridge Inventory (NBI) database for bridge condition rating. NBI database has a large number of attributes for bridge condition rating.
2. Next step is pre-processing of NBI database for separation of data to create training and the testing module for classification and feature selection.
3. The third step is firefly optimization based feature selection of the NBI database for bridge condition rating. Feature selection help to select the best attribute for classification and reduce time complexity and improve accuracy.
4. The next step is the initialization of the CNN network. in this section, we define a layer of CNN and training option of CNN.
5. The fifth step is the training of CNN with selected attributes by feature selection technique and bridge condition rating labeling.

6. Finally, we classify of bridge condition rating with CNN and calculate the performance parameter of proposed work.

5 Results and Discussion

Matrix Laboratory (MATLAB) is used to carry out the simulations for this work. The system configuration is Intel(R) Core i7-7500U-CPU@2.90 GHz, 8 GB-RAM, 1 TB-hard disk, and 64-bit.

Convergence curve is a representation in the form of a graph to evolve the optimization with respect to the number of such individuals. The graph related to convergence history, allows us to know about the optimization problem and its convergence for finding the optimal solution. Convergence curve of Firefly Algorithm shown in Fig. 3. It is a curve between fitness and number of iterations. As can be seen, fitness is maximum (Around 26) when no. of iterations are ≤ 10.

As the number of iterations is increased, the fitness value is decreased to 10 as long as number of iterations is between 11 and 35. After this, when the number of iterations are increased further (36–100), fitness reaches to its lowest value (4) during these instances.

Table 1 provides the values of different parameters like population, iteration, alpha, and Gama used for optimization of firefly algorithm. As is shown Maximum population is taken as 10. Numbers of iterations are taken as 100, the value of alpha is taken as 0.5, and value of gama is taken as 1.

For the measurement of the performance of the CNN network, various performance parameters are needed to be measured, which are explained as below.

\[
\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \quad (7)
\]

\[
\text{Precision} = \frac{TP}{TP + FP} \quad (8)
\]

\[
\text{Recall} = \frac{TP}{TP + FN} \quad (9)
\]

\[
F1\text{Score} = \frac{2 \times (\text{Recall} \times \text{Precision})}{\text{Recall} + \text{Precision}} \quad (10)
\]

where FP is false positive, FN is false negative, TP is true positive, and TN is true negative.

Table 2 summarizes the values of the parameters like accuracy, recall, precision, and F1 score for the proposed CNN model. Fig. 4 provides a bar graph of values of different parameters like accuracy, recall, precision, and F1 score.

Next, we have shown the accuracy of different classes of bridge conditions in Fig. 5. The results indicate that the proposed technique achieves 97.49% accuracy to predict conditions. The accuracy of different classes of Bridge condition ratings are provided by National Bridge Inventory (NBI) database. Different ratings are suggested by bridge condition in terms of Excellent, Very Good, Good, Satisfactory, Fair, Poor, Serious, Critical, Imminent Failure, and Failed.
Figure 6 indicate the training progress plot in terms of the mini-batch loss and RMSE (root mean square error) and the validation loss and RMSE. The loss is the cross-entropy loss. The RMSE is the error of data that the network classifies correctly. RMSE can be calculated as per expression provided by Eq. 11.

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (t_i - y_i)^2}
\]  

(11)

where n length of target/predict data, t target output, and Y network’s prediction for the response. Table 3 provides a comparison of accuracy values of convention CNN model and proposed CNN model. Figure 7 shows performance measures accuracy achieved 97.49% of proposed CNN and comparison with traditional CNN achieved 85% accuracy. It shows our proposed system achieved better performance as compared to traditional work.
Conclusions

The proposed model is designed using the CNN technique exclusive used for artificial intelligence (AI). This method can be exclusively used for the applications like structural health monitoring (SHM), bridge prediction, modeling concrete properties, structural identification, performance evaluation, optimization etc. The proposed CNN model has the learning ability of complicated interrelations amongst leading parameter measures like accuracy, recall, precision, and F1 score and can control the degradation mechanisms and have the ability to precisely monitor the state structure without needing any empirical model. This can lead to significant savings in terms of cost and time. In the present work, a comprehensive model based on the CNN technique is proposed that can easily predict the bridge structure and provide an enhancement in monitoring and control of bridge structure. The firefly algorithm is used as a feature selection technique. For predicting the bridge structure, various parameters like accuracy, recall, precision, and F1 score are taken into account. The value of these parameters is measured and compared with the standard CNN model.

**Table 1** Parameters for the firefly algorithm used for feature selection

| Sr. No | Parameter | Firefly optimization |
|--------|-----------|----------------------|
| 1      | Population| 10                   |
| 2      | Iteration | 100                  |
| 3      | Alpha     | 0.5                  |
| 4      | Gama      | 1                    |

**Fig. 3** Iterations versus fitness function of firefly optimization algorithm for feature selection
Table 2 Performance measure accuracy, precision, recall and F1 score of proposed CNN

| Sr. No | Performance parameter | Parameter value (%) |
|--------|------------------------|---------------------|
| 1      | Accuracy               | 97.49               |
| 2      | Precision              | 98.87               |
| 3      | Recall                 | 96.21               |
| 4      | F1 score               | 97.52               |

Fig. 4 Different performance parameters versus parameter value (%) for CNN

Fig. 5 Accuracy of different classes of bridge condition ratings
Fig. 6  Training progress of convolutional neural network (CNN)

Table 3  Comparison table of accuracy of CNN and proposed CNN

| Sr. No | Technique     | Accuracy (%) |
|--------|---------------|--------------|
| 1      | CNN           | 85           |
| 2      | Proposed CNN  | 97.49        |

Fig. 7  Comparison of accuracy of CNN and proposed CNN
Author's contribution Amit Kumar and Sandeep Singla designed the model and the computational framework and analysed the data. Amit Kumar and Ajay Kumar carried out the implementation and wrote the manuscript with input from all authors. Aarti Bansal and Avneet Kaur helped in analysis and implementation. Sandeep Singla validated all the results in the manuscript. All authors discussed the results and contributed to the final manuscript.

References

1. Garlock, M., Paya-Zaforteza, I., Kodur, V., & Gu, L. (2012). Fire hazard in bridges: Review, assessment and repair strategies. Engineering Structures. https://doi.org/10.1016/j.engstruct.2011.11.002
2. Lewis, P. M. R., & Reynolds, K. (2002). Forensic engineering: A reappraisal of the Tay Bridge disaster. Interdisciplinary Science Reviews, 27, 287–298. https://doi.org/10.1179/030801802225005725
3. Billah, K. Y., & Scanlan, R. H. (1991). Resonance, Tacoma Narrows bridge failure, and undergraduate physics textbooks. American Journal of Physics, 59, 118–124. https://doi.org/10.1119/1.16590
4. Kodur, V. K., Aziz, E. M., & Naser, M. Z. (2017). Strategies for enhancing fire performance of steel bridges. Engineering Structures. https://doi.org/10.1016/j.engstruct.2016.10.040
5. Scheer, J. (2010). Failed bridges: Case studies, causes and consequences. Wiley.
6. ASCE (2017) ASCE infrastructure report card. https://www.infrastructurereportcard.org/cat-item/bridges/
7. Wang L, Yang L, Huang D, Zhang Z, GC.-I.-J. of undefined 2008. An impact dynamics analysis on a new crashworthy device against ship–bridge collision, Elsevier. https://www.sciencedirect.com/science/article/pii/S0734743X07001868.
8. Liu, M., & Frangopol, D. M. (2004). Optimal bridge maintenance planning based on probabilistic performance prediction. Engineering Structures. https://doi.org/10.1016/j.engstruct.2004.03.003
9. Robelin C, S.M.-J. of I. Systems, undefined 2007, History-dependent bridge deck maintenance and replacement optimization with Markov decision processes. Ascelibrary.Org. (n.d.).
10. Naser, M. Z., & Kodur, V. K. R. (2015). A probabilistic assessment for classification of bridges against fire hazard. Fire Safety Journal, 76, 65–73. https://doi.org/10.1016/j.firesaf.2015.06.001
11. Peris-Sayol, G., Paya-Zaforteza, I., Balasch-Parisi, S., & Alo’s-Moya, J. (2017). Detailed analysis of the causes of bridge fires and their associated damage levels. Journal of Performance of Constructed Facilities. https://doi.org/10.1061/(asce)cf.1943-5509.0000977
12. Kodur, V., Gu, L., & Garlock, M. E. M. (2010). Review and assessment of fire hazard in bridges. Transportation Research Record. https://doi.org/10.3141/2172-03
13. Cooper, J. D., Fiedland, I. M., Buckle, I. G., Nimis, R. B., & McMullin Bobb, N. (1994). The Northridge earthquake: Progress made, lessons learned in seismic-resistant bridge design. Public Roads, 58(1), 26–36.
14. Fujino, Y., & Yoshida, Y. (2002). Wind-induced vibration and control of trans-Tokyo bay crossing bridge. Journal of the Structural Engineering. American Society of Civil Engineers. https://doi.org/10.1061/(asce)0733-9445(2002)128:8(1012)
15. Ashto LRFD bridge design specifications, 8th edition (2017). https://store.transportation.org/item/collectiondetail/152.
16. Computational intelligence: A logical approach. Choice Rev Online 1998;35:35–5701–35–5701. doi: https://doi.org/10.5860/CHOICE.35-5701.
17. Kurzweil, R. (2000). The age of spiritual machines: When computers exceed human intelligence. Penguin Books.
18. Michalski, R. S., Carbonell, J. G., & Mitchell, T. M. (2013). Machine learning: An artificial intelligence approach. Springer.
19. Alpaydin, E. (2014). Introduction to machine learning. MIT Press.
20. Robert, C. (2014). Machine learning, a probabilistic perspective. CHANCE, 27(2), 62–63.
21. Marsland, S. (2015). Machine learning: An algorithmic perspective. CRC Press.
22. Kang, F., Liu, X., & Li, J. (2019). Concrete dam behavior prediction using multivariate adaptive regression splines with measured air temperature. Arabian Journal for Science and Engineering, 44, 8661–8673. https://doi.org/10.1007/s13369-019-04095-z
23. Mozumder, R. A., Roy, B., & Laskar, A. I. (2017). Support vector regression approach to predict the strength of FRP confined concrete. Arabian Journal for Science and Engineering, 42, 1129–1146. https://doi.org/10.1007/s13369-016-2340-y
24. Ciresan DC, Meier U, Masci J, Maria Gambardella L, Schmidhuber J. Flexible, high performance convolutional neural networks for image classification. vol. 22, Barcelona, Spain; 2011, p. 1237.
25. Kaur, A., Sharma, S., & Mishra, A. (2019). Performance optimization of cognitive decision engine for CR-based IoTs using various parameter-less meta-heuristic techniques. Arabian Journal for Science and Engineering, 44, 9499–9515. https://doi.org/10.1007/s13369-019-03787-w
26. Sindhu, R., Ngadiran, R., Yacob, Y. M., Zahri, N. A. H., & Hariharn, M. (2017). Sine–cosine algorithm for feature selection with elitism strategy and new updating mechanism. Neural Computing and Applications, 28(10), 2947–2958.
27. Yang, X.-S. (2013). Multiobjective firefly algorithm for continuous optimization. Engineering with Computers, 29(2), 175–184.
28. Al-Thanoon, N. A., Qasim, O. S., & Algamal, Z. Y. (2020). Variable selection in gamma regression model using binary gray wolf optimization algorithm. Journal of Physics: Conference Series, 1591, 012036.
29. Qasim, O. S., Al-Thanoon, N. A., & Algamal, Z. Y. (2020). Feature selection based on chaotic binary black hole algorithm for data classification. Chemometrics and Intelligent Laboratory Systems, 204, 104104.
30. Artificial Intelligence: A New Synthesis. Elsevier; 1998. doi:https://doi.org/10.1016/C2009-0-27773-7.
31. Kleindorfer, P. R., & Saad, G. H. (2009). Managing disruption risks in supply chains. Production and Operations Management, 14, 53–68. https://doi.org/10.1111/j.1937-5956.2005.tb00009.x

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