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

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 equation 1 as:

$$\beta = \beta_0 e^{-\gamma r^2} \tag{1}$$

Here β_0 is the value of attractiveness at distance r = 0. A particular firefly's movement towards a brighter firefly 'j' can be determined by equation 2 as:

$$x_i^{t+1} = x_i^t + \beta_0 e^{-\gamma r^2} ij(x_j^t - x_i^t) + \propto_t \in_i^t \tag{2}$$

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

The case with β_0= 0 is considered as a random walk. Additionally, the randomization parameter $\propto_t$ can be expanded to other distribution functions like L´evy flight function [26].

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:

$$S_x = \sqrt{\left(\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2\right)} \tag{3}$$

Where
$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \tag{4}$$

$$\text{Fitness} = \frac{1}{n}\sum_{i=1}^{n} S_x(X) \tag{5}$$

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.

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 Figure 1.
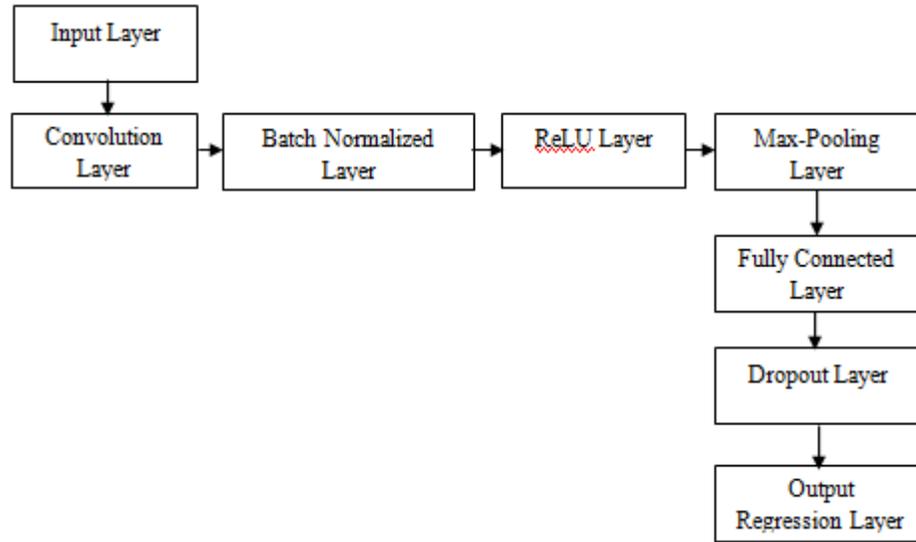
Figure 1: Detailed Schematic for CNN Technique

The detailed description of the CNN layers explained below [27].

- **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**

  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.

- **ReLu Layer**

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

- **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 neutrons 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 0shown 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).

$$MSE = \sum_{i=1}^{R} \frac{(t_i - y_i)^2}{R} \qquad (6)$$

  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 figure 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.
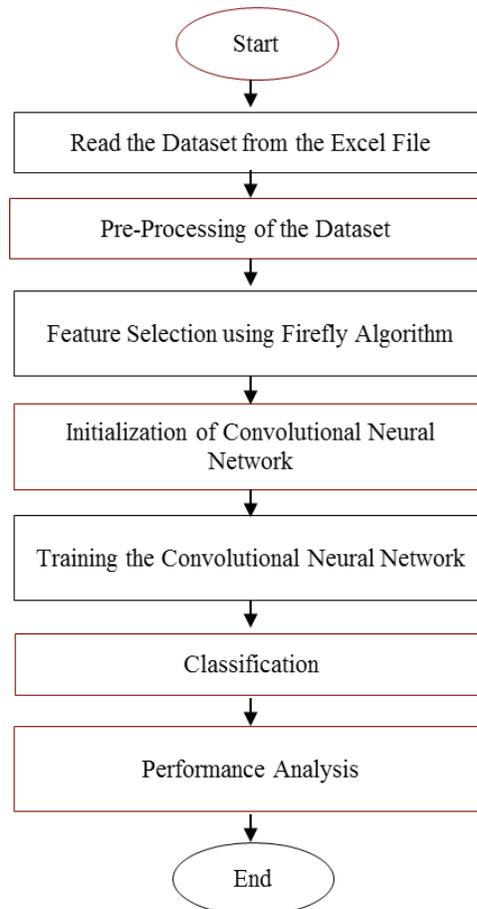
Figure 2: The Flowchart for the Proposed Method

5. RESULTS & DISCUSSION

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 figure 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.
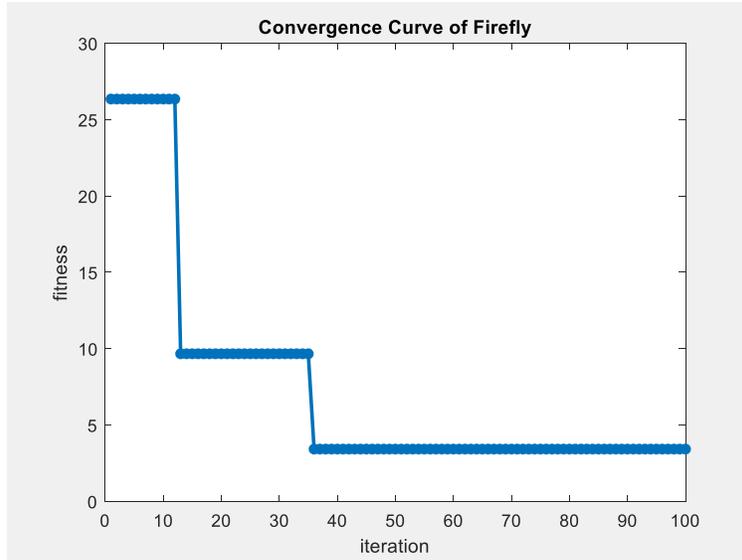
Figure 3: Iterations vs. Fitness Function of Firefly Optimization Algorithm for Feature Selection

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.

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

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

$$Accuracy = \frac{TP+TN}{TP+FP+FN+TN} \tag{7}$$

$$Preecision = \frac{TP}{TP+FP} \tag{8}$$

$$Recall = \frac{TP}{TP+FN} \tag{9}$$

$$F1\ Score = \frac{2*(Recall*Precision)}{Recall+Precision} \tag{10}$$

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. Figure 4 provides a bar graph of values of different parameters like accuracy, recall, precision, and F1 score

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

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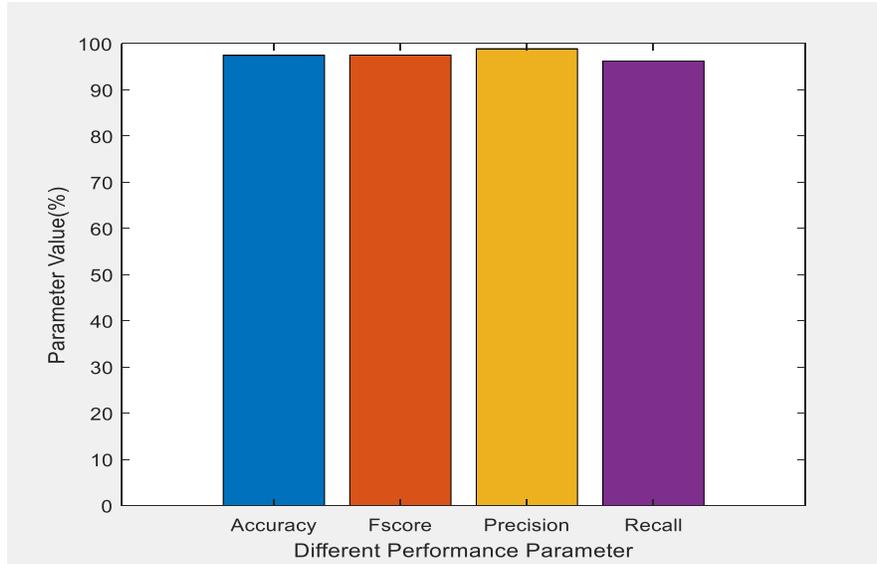
Figure 4: Different Performance Parameters vs. Parameter Value (%) for CNN

Next, we have shown the accuracy of different classes of bridge conditions in Figure 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.
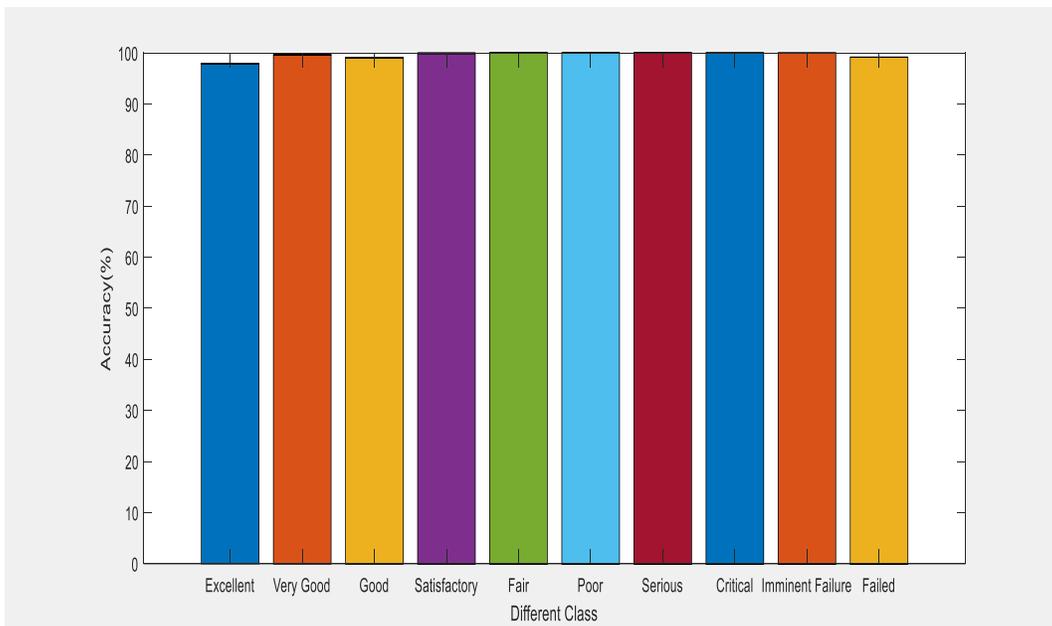
Figure 5: Accuracy of different Classes of Bridge Condition Ratings
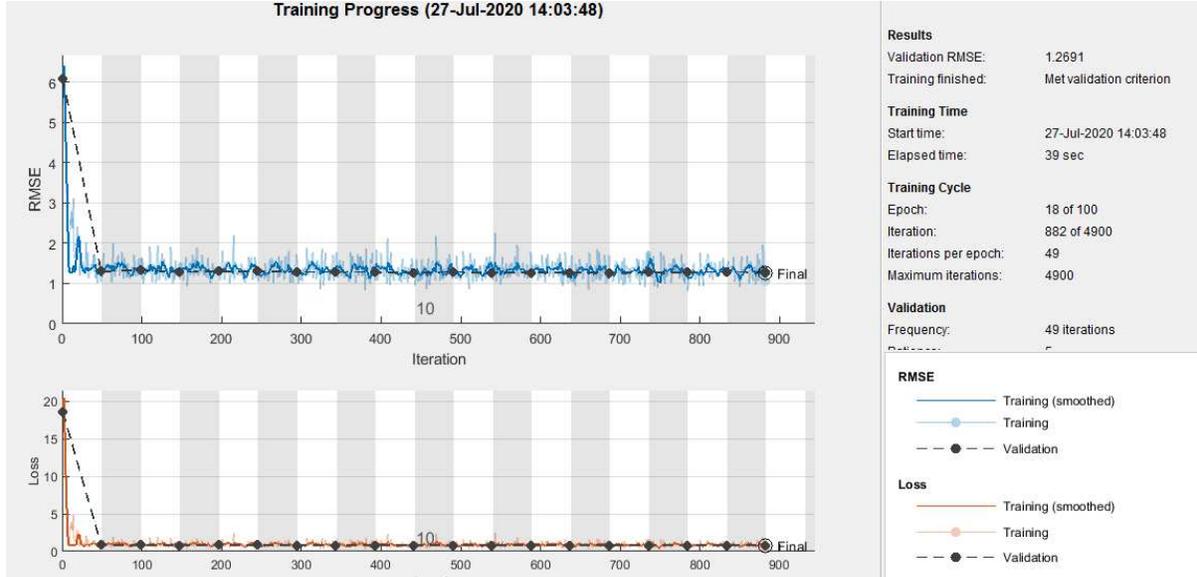
**Figure 6: Training progress of Convolutional Neural Network (CNN)**

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 equation 11.

$$RMSE = \sqrt{\sum_{i=1}^{n} \frac{(t_i - y_i)^2}{n}} \tag{11}$$

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

Table 3: Comparison Table of Accuracy of CNN and Proposed CNN

Sr. No.	Technique	Accuracy (%)
1	CNN	85
2	Proposed CNN	97.49
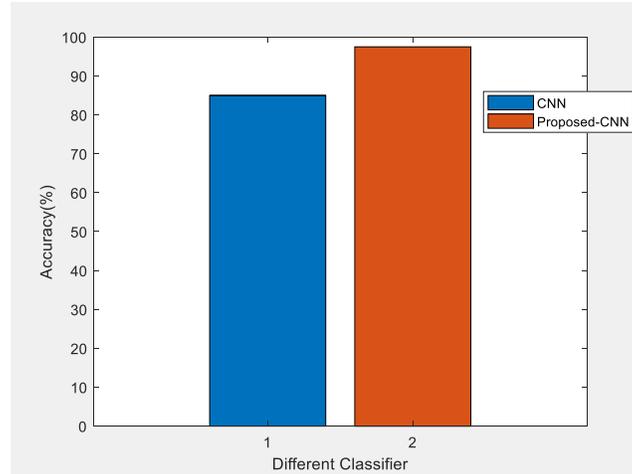
Figure 7: Comparison of Accuracy of CNN and Proposed CNN

6. 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.

Author's contributions Provided in the Manuscript.

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Data Availability Not applicable

Code Availability Not applicable

Conflict of Interest No

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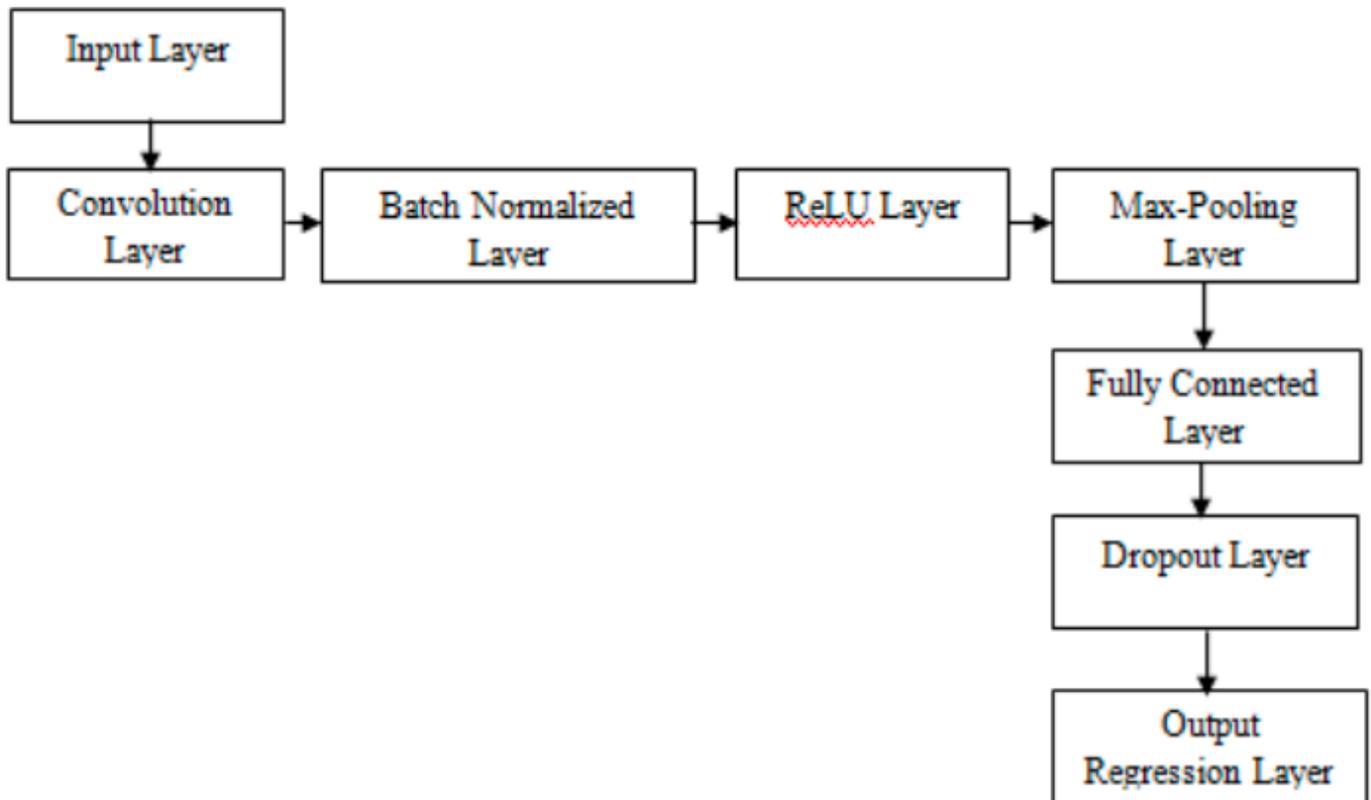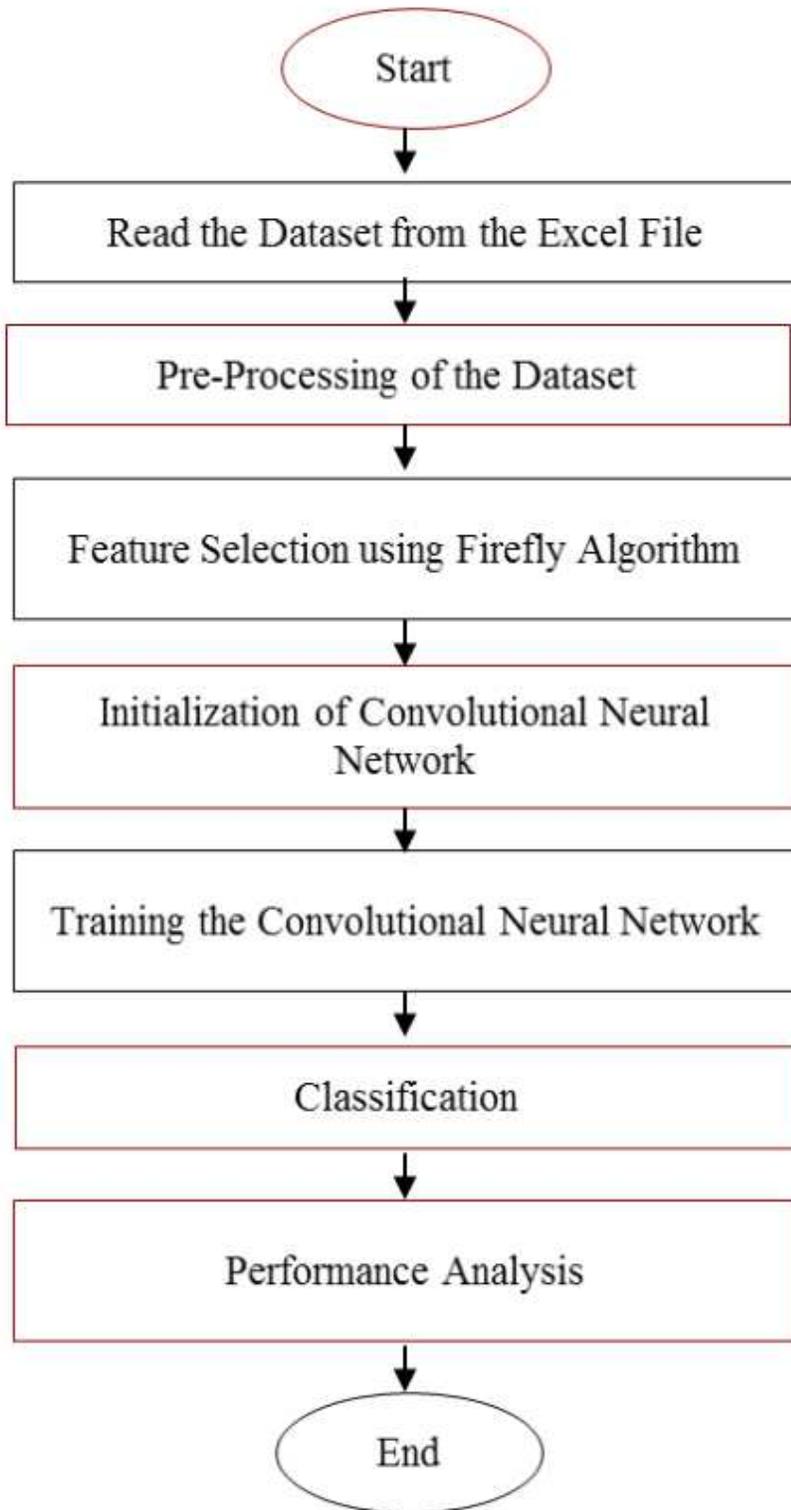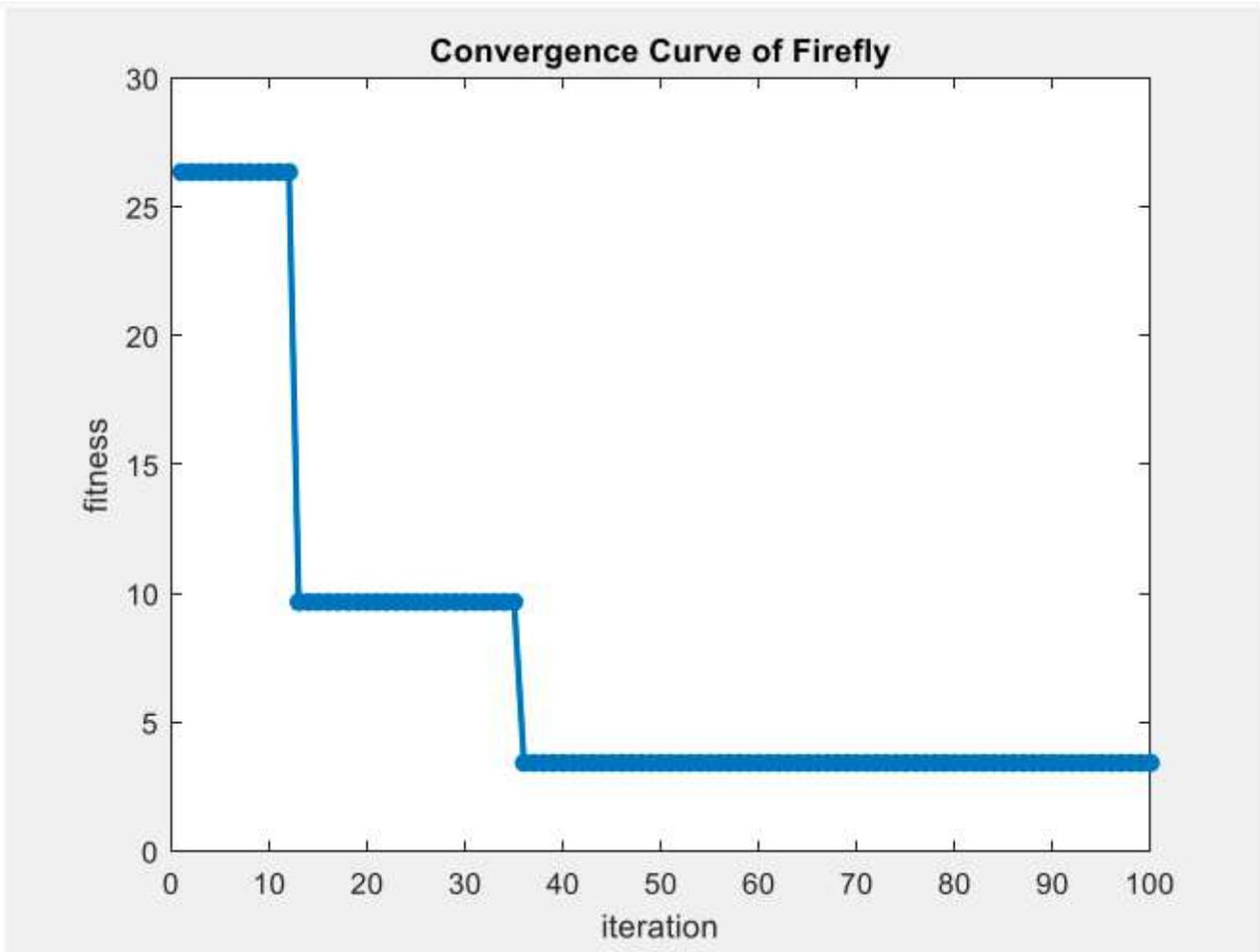
Figures

Figure 1

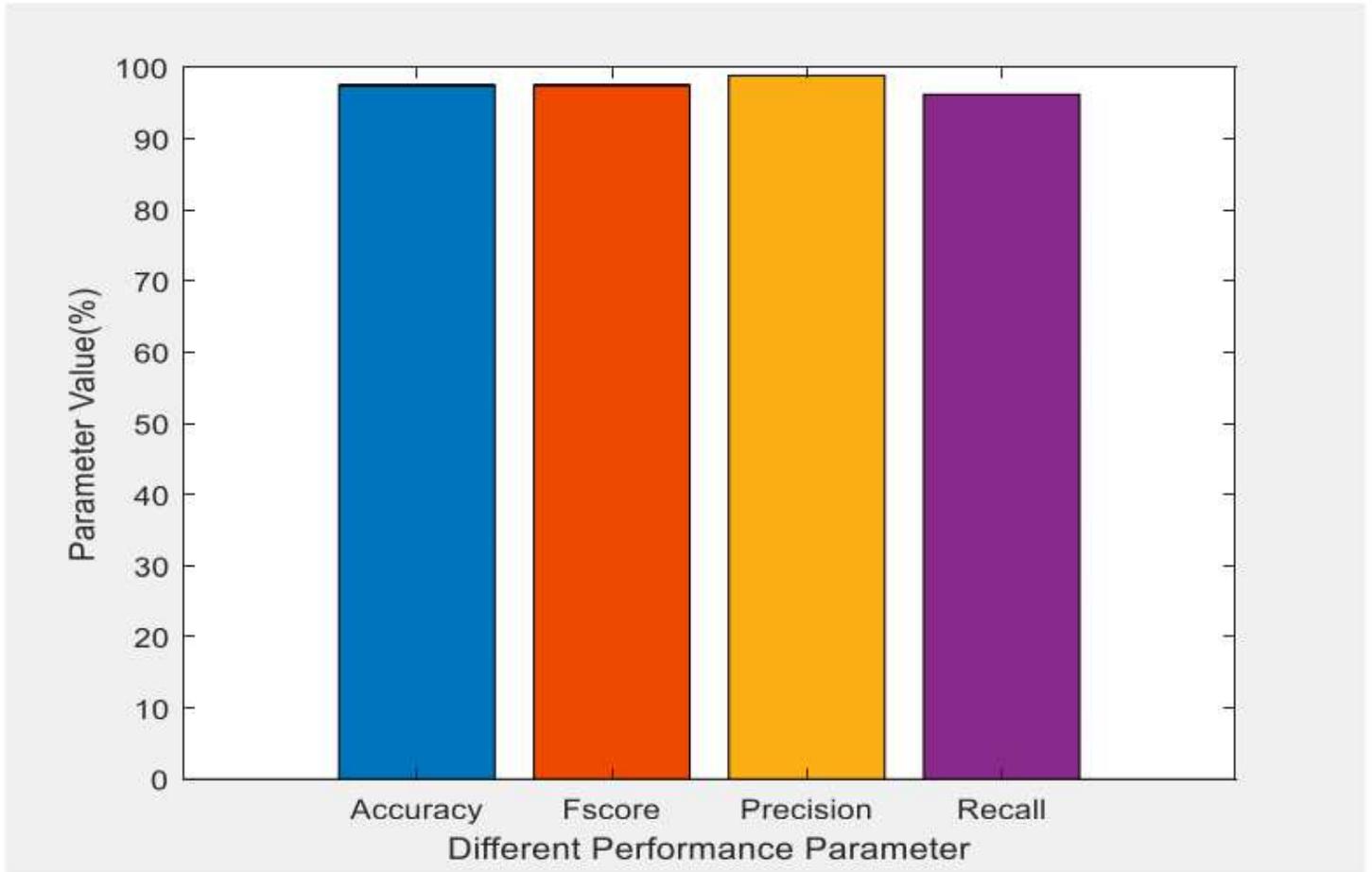Detailed Schematic for CNN Technique

Figure 2

The Flowchart for the Proposed Method

Figure 3

Iterations vs. Fitness Function of Firefly Optimization Algorithm for Feature Selection

Figure 4

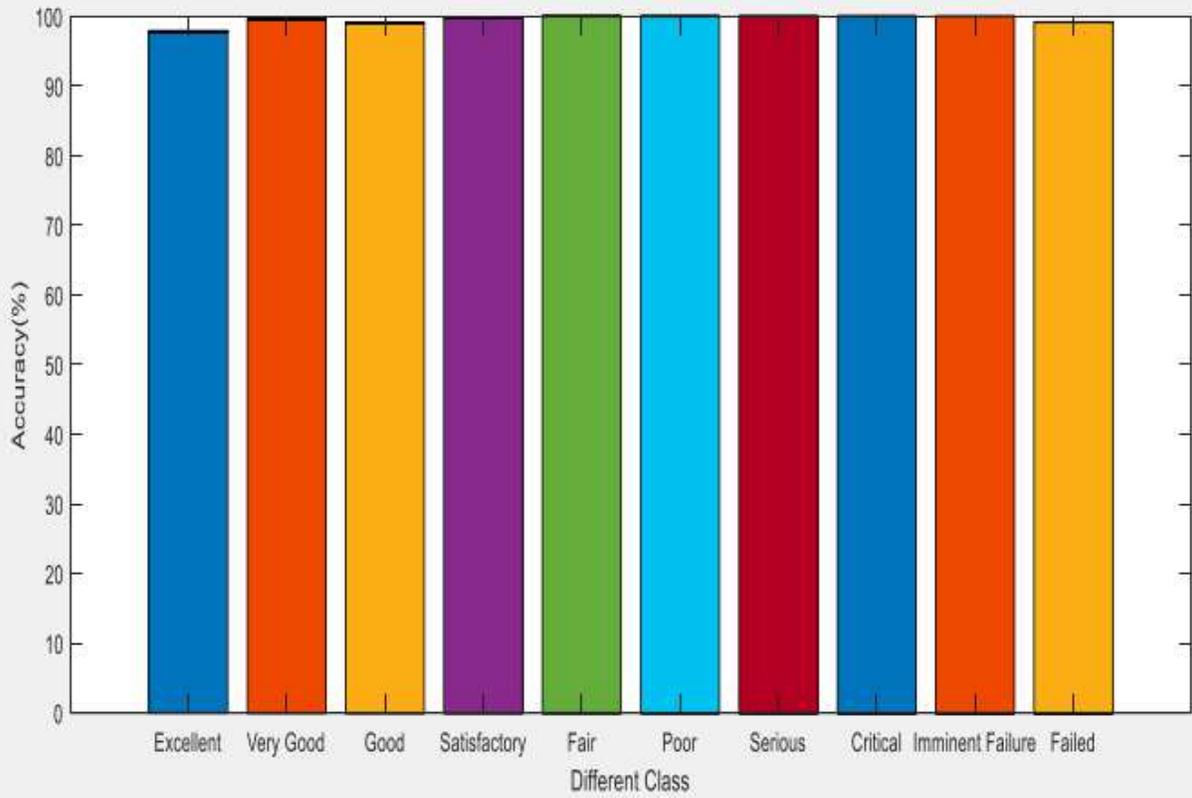Different Performance Parameters vs. Parameter Value (%) for CNN

Figure 5

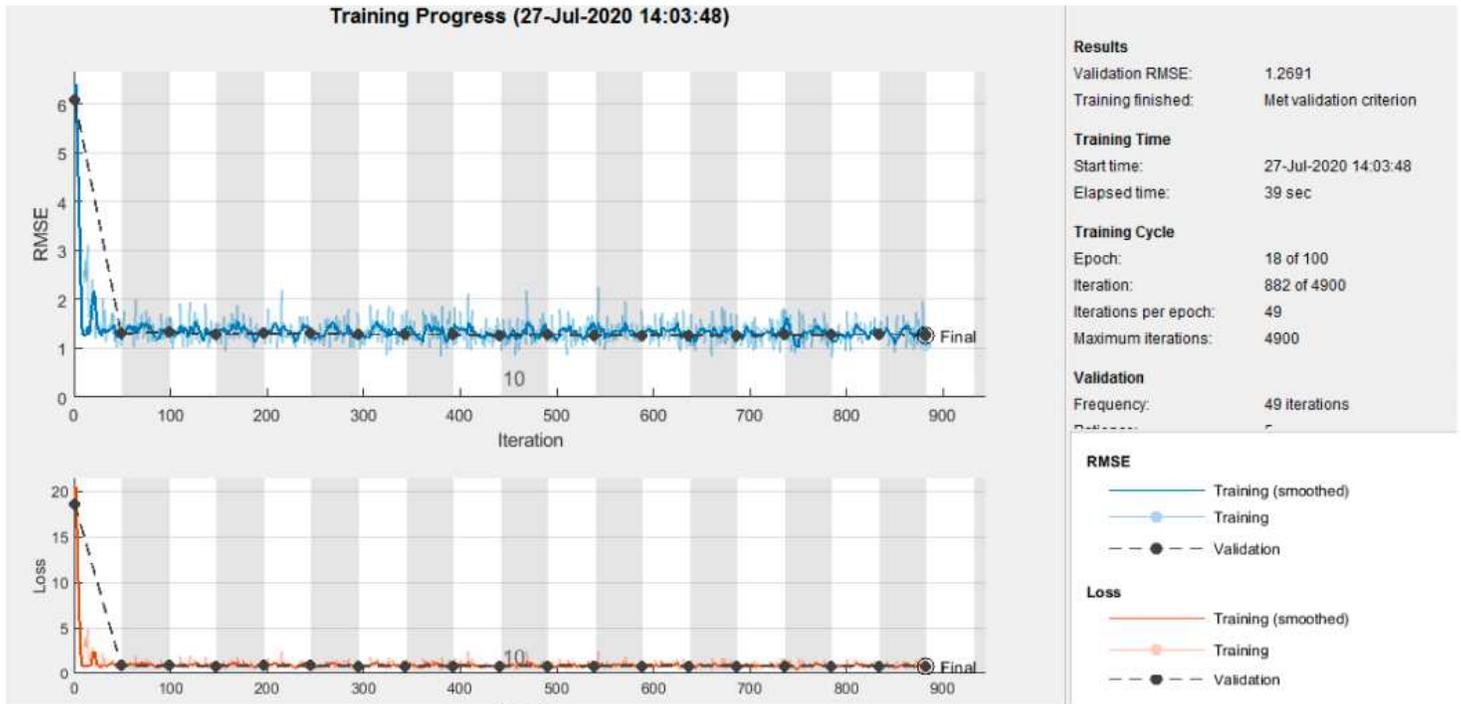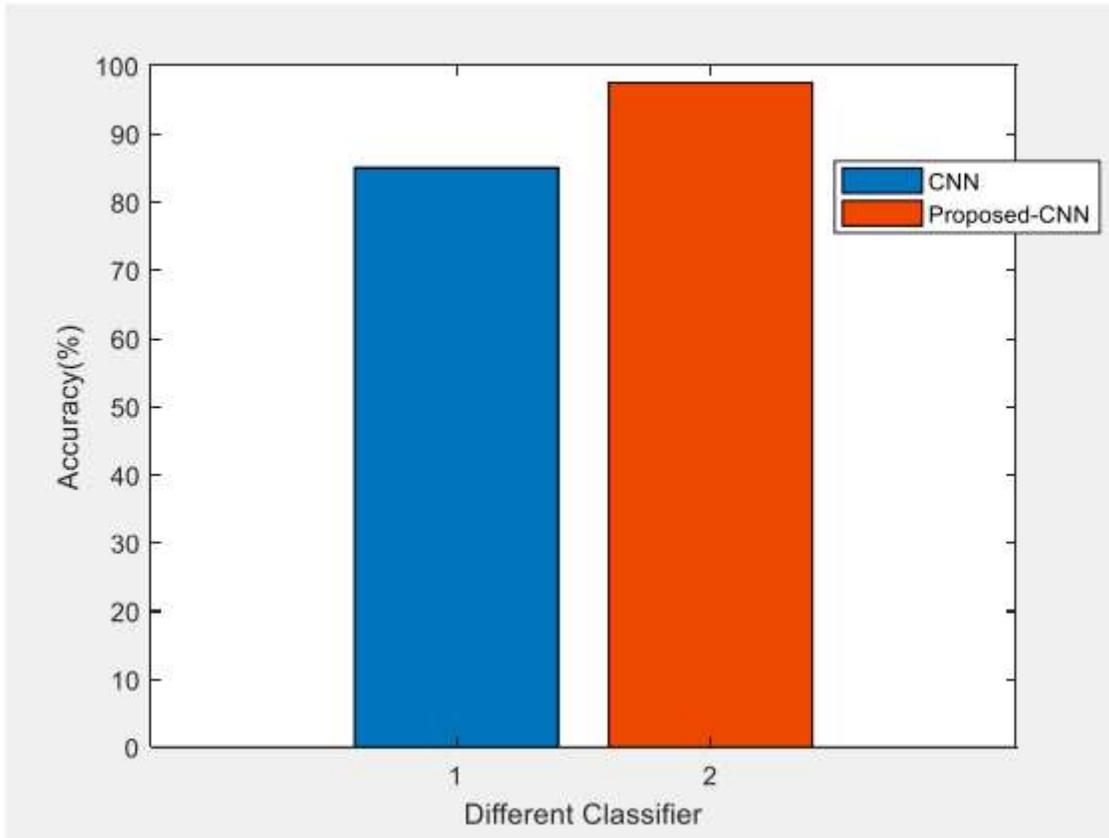Accuracy of different Classes of Bridge Condition Ratings

Figure 6

Training progress of Convolutional Neural Network (CNN)

Figure 7

Comparison of Accuracy of CNN and Proposed CNN