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# Concrete Deck Performance Model based on Hybridization of Ensemble Learning and Artificial Neural Network

**Er. Vipul Spal[1], and Dr. Sandeep Singla[2]**

[1]M.Tech. Scholar, Department of Civil Engineering, RIMT University, Mandi Gobindgarh, Punjab, India
[2]Professor & Head, Department of Civil Engineering, RIMT University, Mandi Gobindgarh, Punjab, India

Correspondence should be addressed to Er. Vipul Spal; vipulspal@gmail.com



**ABSTRACT-** The main aim of the bridge maintenance strategy is to evaluate the performance based on their past conditions and taking appropriate actions for future decisions. Further, taking the appropriate actions at right time reduces the maintenance cost of the bridges. Earlier, man-power-based methods are used for bridge maintenance strategy. However, this method is time consuming, human error while predicting the conditions, and more cost demandable. To overcome these issues, machine learning models-based bridge maintenance strategy are designed in which machine learning models are trained with past conditions of the bridges and future conditions are predict. Thus, this paper proposes a concrete deck performance model based on the hybridization of machine learning algorithm. The main contribution of this work is to enhance the performance of the model by hybrid the prediction of machine learning algorithms. This is achieved by ensemble learning and artificial neural network algorithm. Besides that, feature selection algorithm is applied in the pre-processing of the model. To validate the performance of the proposed model, standard national bridge inventory (NBI) database was taken under consideration and various performance metrics are measured for it. The result shows the proposed model achieves high value of these performance metrics such as accuracy (≅ 0.90207), recall (≅ 0.9363), precision (≅ 0.8855), and F-score (≅ 0.92935) and performance superior over autoencoder and random forest algorithm.

**KEYWORDS-** Artificial Neural Network, Bridge Condition Rating, Concrete deck, Ensemble Learning, Machine Learning.

## I. INTRODUCTION

The demand of the bridges increases globally due to transportation of goods from one place to other and in order to avoid physical obstacles such as railway tracks and dams [1]. On the other hand, maintaining the bridge condition is important because it reduces the maintenance cost, road accidents, and increases the lifetime of the bridge. From 2006 to 2017, the number of national road bridges increased [2] and the overall cost of maintaining structures would increase [3] in Korea, as reported by the "Road Bridge and Tunnel Statistics" of the Ministries of Land, Infrastructure, and Transport in Korea. To achieve this goal, bridge maintenance methods are used. The main motive of the bridge maintenance methods is to monitor the bridge conditions based on the past conditions such as the its maintenance routine, any physical damage, or other constraint which impact the bridge condition. In order to monitor the bridge conditions, manual methods are used and these methods have some limitations, as explained below.

High levels of uncertainty and error also arise from the use of visual inspection methods, the absence of trained people, and the use of discrete condition index criteria for evaluating bridges [1]. If bridges aren't maintained properly, they become unsafe to use. Because of this, several severe accidents have occurred on bridges that were not properly managed, resulting in countless mass fatalities and significant property damage. To rephrase, when a bridge reaches the end of its useful life or collapses, it not only threatens human life but also can paralyze a whole city, leading to enormous financial losses. Bridge and facility upkeep research is being prioritized to reduce the likelihood of such incidents. In the present time, advance methods such as machine learning model-based bridge maintenance methods are used for bridge monitoring.

In the literature, machine learning models are successfully applied for design concrete deck performance model. These models rate the bridges in the scale of 0-9 [4]. The 0-scale value represents bridge is very low-quality condition whereas 9 scale value represents the bridge is very good quality condition. In the literature, convolutional neural network, support vector machine, autoencoder, random forest, and artificial neural network [5-9]. Further, nature inspired algorithms are hybrid with these algorithms to enhance its performance [10]. The performance measurement using the single machine learning model impact the robustness of the model. Therefore, in this research hybridization of machine learning models is done. The main contribution of this paper is to hybrid the machine learning models to enhance the performance of concrete deck model. To achieve this goal, ensemble learning and artificial neural network was taken under consideration. Besides that, pre-processing on the dataset was done to extract the appropriate features using feature selection algorithm. Further, the ensemble learning and artificial neural network algorithm was trained and tested using the standard dataset. Next, the output of both models was hybrid for classify the bridge condition rating. In the last, the performance analysis of the proposed model was done using various performance metrics. The result shows the proposed model achieves high value of these performance metrics such as accuracy ($\cong 0.90207$), recall ($\cong 0.9363$), precision ($\cong 0.8855$), and F-score ($\cong 0.92935$) and performance superior over autoencoder and random forest algorithm.

The rest of the paper is organised as follows. Section 2 gives an overview of ensemble learning, artificial neural network, and feature selection algorithm. Section 3 explains the proposed concrete deck performance model. Section 4 shows the simulation evaluation and comparative analysis with the existing models. Finally, conclusion is drawn in Section 5.

## II. INTRODUCTION TO ENSEMBLE LEARNING AND ARTIFICIAL NEURAL NETWORK

In the proposed model, the hybridization of ensemble learning and artificial neural network is done. Therefore, in this section, an overview of ensemble learning and artificial neural network is given to understand the proposed model. After that, a detailed description of feature selection algorithm is given.

### *A. Ensemble Learning*

In Ensemble Learning, several separate learners are combined into one. This learner could be a Naive Bayes classifier, a NN, or a DT, among other options [11]. Ever since the 1990s, the use of "ensemble learning" has been on the rise. While opposed to a single learner, a group of students is always preferable when completing a task. In the MATLAB, fitcensemble function is available to use ensemble learning (fitcensemble(Tbl,ResponseVarName). This function in response returns the trained classification model object (Mdl) consists of boosting 100 classifcation trees results along with the response data and predictor in the table Tbl. In Tbl, the name of the response variable is denoted by ResponseVarName and by default LogitBoost is used in fitcensemble for binary classification and for multiclass classification the AdaBoostM2 is used.

### *B. Artificial Neural Network*

ANNs are derived from the study of human brain's functions [12]. A network of nodes (neurons in ANNs) is constructed by layering and linking them in various configurations. Among the three layers are input, hidden, and output, which are all distinct. Figure 1 depicts a network's structure or layout in all its details. It was common practise to refer to neural networks as "single-layer neural networks" or "thin neural networks," because of their little layered architecture. It's also known as "deep neural networks," "multi-layer neural networks," or simply "deep neural networks." It is now common practise to use deep neural networks in real-world applications. Nodes from another hidden layer are connected with each input node. To show this, the arrowhead in Figure 1 is connected to a specific weight. In order to build the network, we use two alternative methods: backpropagation and feedforward propagation. Feedforward propagation is the first step in training a network. The inputs and outputs from the training examples are fed into the neural network. Finally, the weights of the neural network are randomly assigned to provide results depending on the inputs. In order to determine the error, the neural network's results are compared against the real results. Backpropagation is the process of updating the weights based on each node's contribution to the mistake and adjusting the weights appropriately to lower the error. Thes' two processes are continued until all of the training data has been processed. As a result, the neural network improves its ability to learn from previous instances.

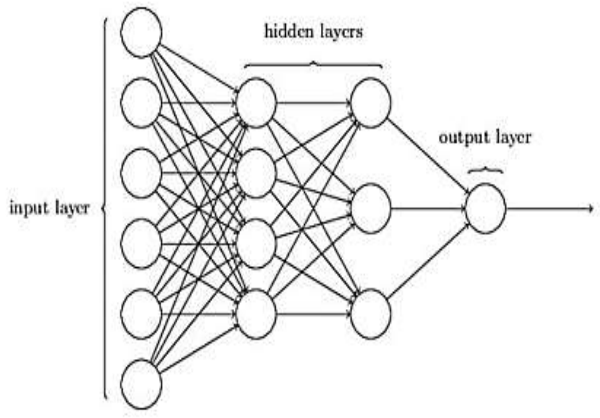


Figure 1: ANN Architecture (Adapted from [12])

### *C. Feature Selection Algorithm*

There are different variables in the dataset, but while the user is developing an ML model, they use few variables for building it and the rest are discarded. The discarded features are either irrelevant or redundant. If the irrelevant and redundant features present in the dataset are given as input to the model then the overall accuracy or performance of the model gets affected negatively. Due to this, identifying and selecting appropriate features from the input and removing the irrelevant features is an important task done through ML. There are two types of features selection algorithm supervised and unsupervised [13]:

- **Supervised Feature Selection technique**: This approach consider the target variable and it can be used for labelled dataset.
- **Unsupervised Feature Selection technique**: This approach ignores target variables and can be used for unlabelled datasets.

Further, we have discussed the sub-fields of supervised feature selection technique.

- Wrapper Method: In this, features are selected by considering it as search problem by making different combinations then compared it after evaluating with other combinations. The training of algorithm is performed using subset of features iteratively and the based-on output of the model features are either added or subtracted. Then model is again trained using these feature set. There are different wrapper methods: backward elimination, recursive feature selection, forward selection and exclusive feature selection.
- Filter Method: In this method, statistics measures are used for selecting features without its dependency on the learning algorithm. It chooses features as a pre-processing step and use different metrics through ranking for filtering out the irrelevant feature and redundant columns from the models. The

benefit of using this method is the low need for computational time and not overfitting the data. There are various filter methods: missing value ratio, Chi-square test, correlation coefficient, Fisher's score and missing value ratio. The correlation coefficient is used in the proposed model in which measurement of 2 or more variables linear relationship is measured for predicting one variable from another. The idea behind using this filter method for selecting feature is that the good variables are highly correlated with the target. Furthermore, variables and targets need to be correlated with each other but should be uncorrelated among them. As, one variable can be predicted from the other if two variables are correlated. So, model only need one of them in case of correlated two features as second one adds no additional information.

- Embedded methods: This method is made by combination of advantages of both filter and wrapper methods having features interaction and low computational cost. These methods are fast in processing same as filter methods but give more accurate results then it. Also, these iterative methods enable it to evaluate each iteration and find the most important features that contribute the most to training it in a particular iteration. Random forest and regulation are the most important embedded methods.

## III. PROPOSED CONCRETE DECK PERFORMANCE MODEL

In this section, the proposed model is explained that designed for predict bridge deck performance. The flowchart of the proposed model is shown in Figure 2.

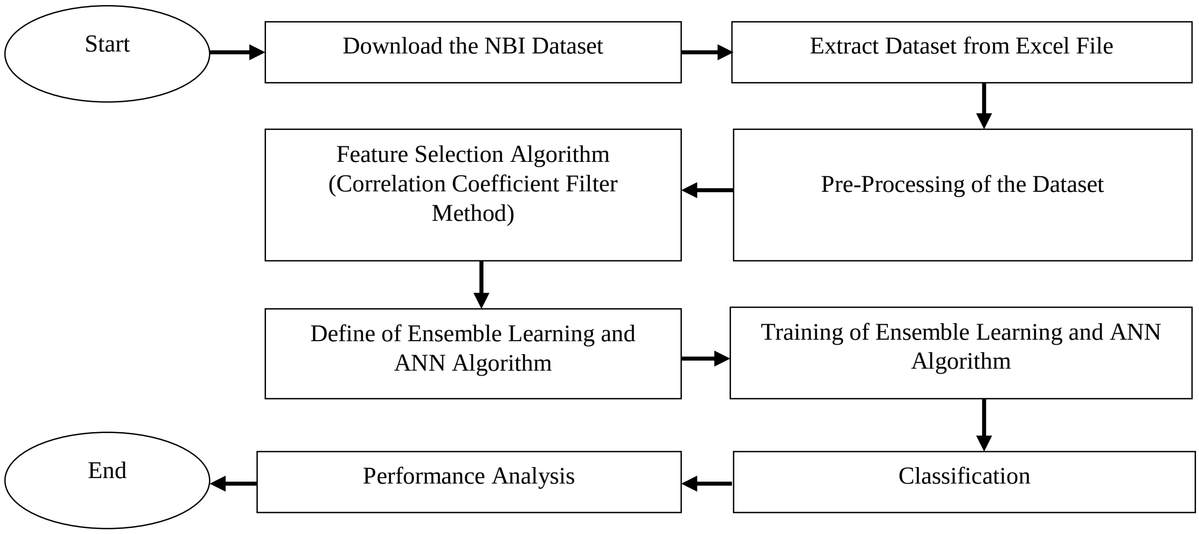


Figure 2: Proposed Model for Bridge Condition Rating

The detailed description of proposed model is explained below.
In the first step, the database information is read from the excel file. In the proposed model, National Bridge Inventory (NBI) database is taken under consideration for bridge condition rating [77]. The NBI database contains a large number of attributes which represents the information of bridge parameters. Out of these some attributes plays an important role in bridge condition rating. Therefore, in the second step, the pre-processing of NBI database is done. In the pre-processing of database, most appropriate features are selected using feature selection for machine learning algorithms and the database is separated into training and testing module for classification purposes. In the third step, feature selection (IFS) algorithm is applied for feature selection of NBI database for bridge condition rating. The feature selection help to select the best attribute for classification and reduce time complexity and improve accuracy. In the proposed model, correlation coefficient is used for feature selection. In the fourth step, the initialization of machine learning algorithm is done for bridge condition rating. The algorithms are taken under consideration are ensemble learning and artificial neural network. In the fifth step, the training of ensemble learning and artificial neural network with selected attribute by feature selection algorithm and bridge condition rating labeling is done. In the sixth step, we have classified of bridge condition rating with ensemble learning and artificial neural network and combine both output for final prediction. In the seventh step, the performance analysis of the proposed model is done using accuracy, recall, precision, F-score.

## IV. SIMULATION EVALUATION

In this section, the simulation evaluation of the proposed concrete deck performance model is shown and compared with the existing models on the standard dataset. The proposed model was simulated in MATLAB software. The setup configuration of the proposed model is explained in Table 1.

Table 1: Setup Configuration

| Parameter | Values |
|---|---|
| ANN Network | Feedforward |
| Number of Neurons | 10 |

Further, Table 2 explains the performance parameters are determined for the proposed model.

Table 2: Performance Parameters [14-15]

| | |
|---|---|
| Accuracy | $Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$ |
| Precision | $Precision = \frac{TP}{TP + FP}$ |
| Sensitivity or Recall | $Sensitivity = \frac{TP}{TP + FN}$ |
| F1-Score | $F1 - Score = 2 * \frac{Precision.Recall}{Precision + Recall}$ |

Next, Table 3 shows the performance analysis of the proposed model using various parameters.

Table 3: Performance Analysis of the Proposed Model

| Parameter | Proposed Model |
|---|---|
| Accuracy | 0.90207 |
| Recall | 0.9363 |
| Precision | 0.8855 |
| F-Score | 0.92935 |

In the last, the proposed model is compared with the existing models are designed using machine learning algorithms. The machine learning algorithms are taken under consideration for comparison purposes are “auto encoder” and “random forest”.

Figure 3-6 shows the proposed model achieves the highest accuracy, precision, recall, and F-score value over the other models based on machine learning algorithms.

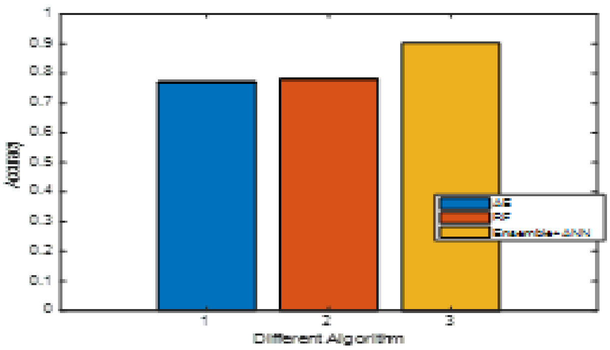


Figure 3: Comparative Analysis based on Accuracy Parameter

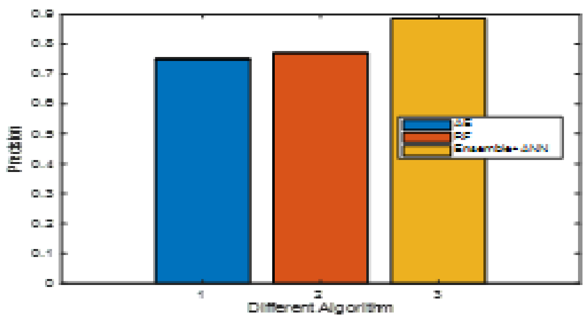


Figure 4: Comparative Analysis based on Precision Parameter

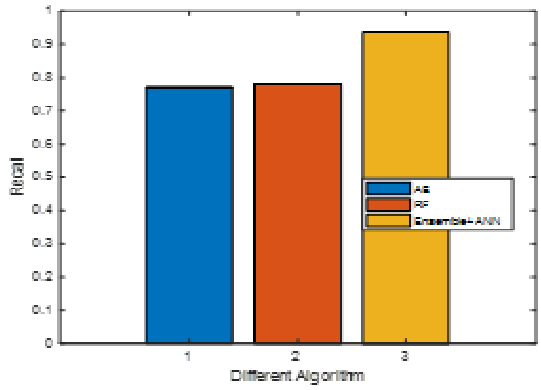


Figure 5: Comparative Analysis based on Recall Parameter

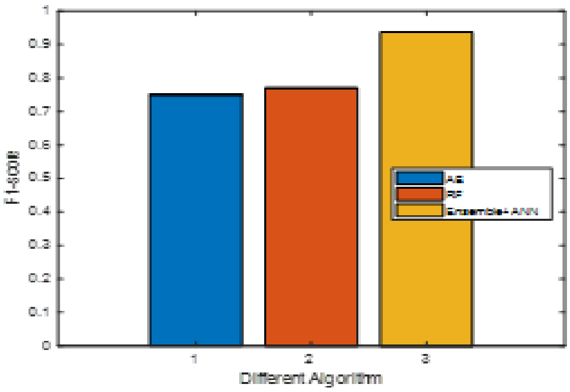


Figure 6: Comparative Analysis based on F1-Score Parameter

## V. CONCLUSION

In this paper, we have hybrid the two machine learning algorithms such as ensemble learning and artificial neural network for concrete deck performance in terms of their rating. The rating varies from 0-9. Besides that, feature selection algorithm was used for feature selection. After that, both machine learning models were trained and tested. In the last, output of both algorithms is hybrid to get the final prediction in the output. The result shows that the proposed model achieves high accuracy ($\cong$ 0.90207) over autoencoder ($\cong$ 0.77) and random forest ($\cong$ 0.78).

## CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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