Hybridization of Machine Learning Algorithms to Predict of Concrete Bridge Deck Performance

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Abstract: In this paper, we have developed a prediction model for bridge condition rating. To achieve this goal, feature selection and hybridization of machine learning algorithm is done. The feature selection is done using infinite feature selection algorithm to select most appropriate features of the bridge. Further, decision tree and KNN machine learning algorithm is taken under consideration for bridge condition rating purposes. The simulation evaluation is done on standard NBI database and three performance metrics such as accuracy factor, mean absolute error, and mean square error are determined. The result shows that the proposed model achieves lower value of these parameters over the existing models such as “artificial neural network (ANN)”, “Markov Model”, “Hidden Markov Model”, and “Semi-Markov Model”.

Keywords: *Concrete Bridge Deck Performance, Decision Tree, Infinite Feature Selection, KNN Algorithm, Machine Learning, National Bridge Inventory Database*
DOI: 10.53555/ecb/2022.11.03.18

1. Introduction

Bridges have a tremendous impact on the US economy. In the United States, there are more than six hundred thousand bridges in operation. Almost a third of them are deemed structurally poor and will cost over than $164 billion to fix or replace. Identification of the parameters that influence the performance of concrete bridge decks throughout the course of their service life is crucial for the creation of an appropriate quality evaluation and degradation forecasting model. An accurate bridge deck degradation model may help forecast the short and long-term behaviour of concrete bridge decks, hence reducing the need for expensive regular inspection and repair operations [1-2].

Visual inspections, probing, non - destructive procedures, and structural health monitoring (SHM) are just a few of the technologies that have been developed over the years to help with monitoring the condition [3]. Damage to the bridges is quantified and communicated using performance indicators (PIs), that are metrics that identify the condition status of the bridge part qualitatively and/or quantitatively [3]. Faleschini et al.[3] divided the PIs into operational and research divisions. [4] Operational indicators rely on qualitative state evaluations that identify the as-built state and the other values reflect deviations from this state. [4] As a result of this quantitative examination of the structural safety of an asset's assets, a particular limit state's likelihood of failure is calculated [3].

There's been a variety of forecasting models created to determine how long bridge components will last based on the differences in PIs. Some examples of frequent processes impacting reinforced concrete buildings are corrosion caused by chloride [5–8], corrosion caused by carbonation [8–9], alkali-aggregate interaction [10–11], and freeze/thaw attack. Another technique proposes utilizing the reliability coefficient as an indication of bridge reliability and building a reliability profile, defined as the fluctuation of the reliability index over time at a degradation rate following the deterioration start time [12,13].

Because transportation agencies have to manage so many assets, research PIs and their accompanying forecasting models provide a more quantitative estimate of the deteriorating phenomenon, but their practical use on BMS is still restricted. This means that current BMS models rely heavily on operational PIs, or condition ratings, as input variables for the degradation models [2].

There is a wealth of published material on degradation modelling methodologies that are based on condition ratings. Some examples of this material include, but are not limited to the following: deterministic models (multiple linear regression [14], polynomial regressions [14–16], ordinal logistic regression [17], stochastic models (Markov models [18–21], semi-Markov models [20–22], hidden Markov models [HMMs] [20,23], artificial intelligent (AI) techniques (artificial neural networks [ANNs][24–26], fuzzy logic [26,27] case based reasoning [28], Bayesian networks[29], and Petri nets [30].

The main contribution of this paper is to design a prediction model for predict the performance of concrete bridge deck. To achieve this goal, initially, database is read. National Bridge Inventory (NBI) database is taken under consideration. After that, pre-processing is done on the database by feature selection algorithm. Feature

selection algorithm assists in selecting the optimal attribute for prediction, reducing time complexity and increasing accuracy. In this work, we have chosen infinite feature selection algorithm. After feature selection, two machine learning algorithms are taken under consideration such as decision tree and k-nearest neighbour (KNN). These algorithms are trained based on the selected features and bridge condition rating is done. The final bridge condition rating is done by hybrid the results of both machine learning algorithms. In the last, the performance analysis of the proposed method is done using accuracy factor, MSE, and MAE. The result shows that the proposed method is superior over the existing methods.
The remaining paper is organized as follows. Section 2 shows related work. Section 3 explains the preliminaries. Section 4 illustrates the proposed model. Section 5 shows the simulation evaluation. Conclusion and future scope are drawn in Section 6.

2. Related Work

The prediction of concrete bridge deck performance in the early phase helps in estimation of optimal maintenance, rehabilitation, and replacement strategies. In this section, we have studied and analysed some recent research articles to understand how machine learning algorithms are deployed for bridge condition rating.

Lu et al. [31], Bridge component ratings can be forecasted using an ordinal logistic regression model. For its capacity to accommodate ordinal component evaluations of bridges, regression analysis's explanatory strength, and predictive precision, the model is selected. Multiple linear regression and logistic regression techniques were used to predict the ratings of three bridge components in this investigation. If and when element-level data becomes accessible, the multinomial logistic model described in this study may be simply used. All eight assessment criteria were evaluated using both in-sample and exterior validation analyses. Furthermore, the ordinal logistic regression technique is shown to be more accurate than the multiple linear regression method when it comes to anticipating bridge component ratings. As a result, it is better able to accurately forecast future events than other methods because of this.

Nguyen et al. [32], Bridge repair, maintenance, and rehabilitation cannot proceed without a precise forecast of the future state of structural components. Predicting future deck condition for bridge structures in Alabama, the United States, using Artificial Neural Networks (ANN) was the subject of this paper. From the National Bridge Inventory database (NBI), 2572 bridges were retrieved and utilised to train and validate the Artificial neural network with eight model parameters and one output, the deck grade. Average Daily Traffic, Current Bridge Age, Design Load, Approach Span Design, Main Structure Design, Number of Main Spans, Average Daily Traffic Growth Rate, and Percent of Daily Truck Traffic are the eight input variables. A 73.6 percent accuracy rate was found in the results of using the ANN model to forecast bridge deck condition. Using a margin of error of 1 increased the suggested model's accuracy to 98.5 percent. In addition, a sensitivity analysis of the input parameters indicated that the most significant determinant of the bridge deck rating was the Current Bridge Age. The Design Load and Main Structure Design were then completed. The ANN's performance was found to be unaffected by the other input parameters. Last but not least, it was demonstrated that the ANN can be utilized to generate the bridge deck degradation curve that aids in visualizing a deck's condition rating and corresponding upkeep requirements for the remaining life span of the bridge.

Kumar et al. [33], An artificial intelligence (AI) model based on convolutional neural networks was created in this research. Predicting a bridge's construction using this model is more accurate than doing real tests. The firefly algorithm is a feature selection strategy that ensures high accuracy. National Bridge Inventory (NBI) data is used to populate the database. It is important to take into account many performance indicators including accuracy, recall, precision, and the F1 score in order to accurately forecast the construction of a bridge. In order to compare the suggested CNN model to the traditional CNN model, these parameters were measured using the proposed CNN model. The suggested model has a much higher accuracy (97.49 percent) than the traditional CNN model (85 percent).

G. Morcous [34], In order to forecast the future state of bridge components and networks, bridge management solutions have incorporated Markov-chain models. Based on two assumptions, these models were developed. As an initial matter, bridge inspections are carried out on a regular basis, according to preset schedules (i.e., constant inspection period). Second, the state of the bridge in the future is only dependent on the current state and not on the status of the bridge in the past (i.e., state independence). Data from the Quebec Ministry of Transportation is used in this study to examine the effect of these assumptions on the predicted performance of bridge deck systems. As the inspection period changes, Bayes' rule is used to alter transition probability matrices for the various parts of the deck system. Variability in examination interval may lead to 22% inaccuracy in forecasting bridge deck system lifetime, according to this study. Markov chains' state independence assumption was tested statistically and found to be acceptable with a 95% confidence level, which is appropriate for network analysis.

Abdelkader et al. [35], A hybrid Bayesian-based approach for forecasting concrete bridge deck performance was provided in this research. Inspection data from the Quebec Ministry of Transportation are the basis for this new approach. Markov Chain probability distributions include Latin hypercube sampling and a Bayesian belief network to handle the stochastic character of transition probabilities employed in the approach. Results show that Bayesian belief networks allow the evaluation of the severity of the discovered flaws on the overall condition of the bridge deck. Delamination, cracking and spalling are all examples of bridge flaws. For P11, P22, and P33, a Metropolis-Hastings method is used to compute posterior distributions of the in-state probabilities. For ease of usage, a computerized tool has been designed for the user. The suggested technique outperformed the generally used Weibull distribution, whereas the proposed model improved the RMSE, MAE, and X2 by 46.885 percent, 45.078% percent, and 87.062 percent correspondingly. On the basis of the comparison, it seems that the suggested strategy has the potential to accurately anticipate future outcomes. This new model aids in accurately predicting the future health of bridge decks, allowing for better planning of repair work, maintenance, and rehabilitation efforts, as well as better decision-making at both the project and element levels.

3. Preliminaries

Here, the suggested strategy is discussed using infinite latest feature selection, decision trees, and KNN algorithms.

3.1 Infinite Latest Feature Selection Algorithm

The Inf-FS is a graph-based technique that uses power series matrices to assess the relative significance of a feature in relation to all other features combined [36]. There are nodes for characteristics and weighted edges for connections between them in the Inf-FS model's affinity graph. Each l-th route across the graph is seen as a potential selection of characteristics to be considered. It is thus feasible to investigate the relevance of each subset of traits by altering these pathways and allowing them to reach an unlimited number. Each feature in the original set is given a final score by the Inf-FS, with the score reflecting how well the feature fits the classification job. Researchers may then execute subset feature selection during a model selection stage by ordering the results of the Inf-FS in the order they were ranked in the Inf-FS.

3.2 Decision Tree Algorithm

There are several ways to solve regression and classification issues using Decision Trees, although they are most often employed for Classification difficulties [37]. An internal node represents a characteristic of a dataset, branches reflect the decision rules, and each leaf represents a specific result. There are two nodes in a Decision tree: the Decision Node and the Child Nodes. Child nodes represent the results of choices, while Decision nodes have been used to create decisions and include several branches. Based on the dataset's characteristics, choices or tests are made. Using this tool, one may find out all of the potential outcomes to a specific situation or choice. The following steps describe how a decision tree works. Rather of starting at the top of the tree and working down, a decision tree algorithm begins at the bottom and works its way up. Comparative analysis between the root attribute and the record attribute, this method moves to the next node in a branch.

To get to the next node, the algorithm compares the value of the property to the values of the other subnodes. It keeps going until it approaches the leaf node of the tree and then stops.

3.3 KNN Algorithm

An example of a supervised machine learning method is the K closest neighbours (KNN) algorithm [38]. The purpose of a supervised machine learning method is to train a function such that f(X) = Y, where X is the input and Y is the result. It's possible to utilize KNN for both classification and regression using the same model. KNN is a non-parametric learning algorithm that does not need a large amount of data to be analysed. The term "lazy learning" refers to the fact that the learning process for the algorithm takes essentially little time since it just retains the data from the training phase (no learning of a function). After that, the data that has been saved will be used for the purpose of the assessment of a new query point. Any distribution is assumed to be non-parametric in nature. Thus, KNN doesn't have to discover any parameters for the distribution. It is possible to identify new parameters for prediction using the parametric approach. Because of the necessity for comparison, the sole hyperparameter that KNN has is K (the number of points that must be taken into account). The KNN algorithm's workings is outlined here.

During the phase known as "training," the model will be responsible for storing the data points. During the testing phase, the classification of each point in the test dataset is accomplished by computing the distance between the query point and each point from the training phase. It is possible to compute a variety of distances, including the Manhattan distance, the Hamming distance, and the Chebyshev distance; nevertheless, the Euclidean distance is by far the most common (for smaller dimension data). The formula for calculating the Euclidean distance between two points, a query point (q) and a training data point (p), is as follows:

$$ED = \sqrt{\sum_{i=1}^{n}(p_i - q_i)^2} \quad (1)$$

4. Proposed 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 1.

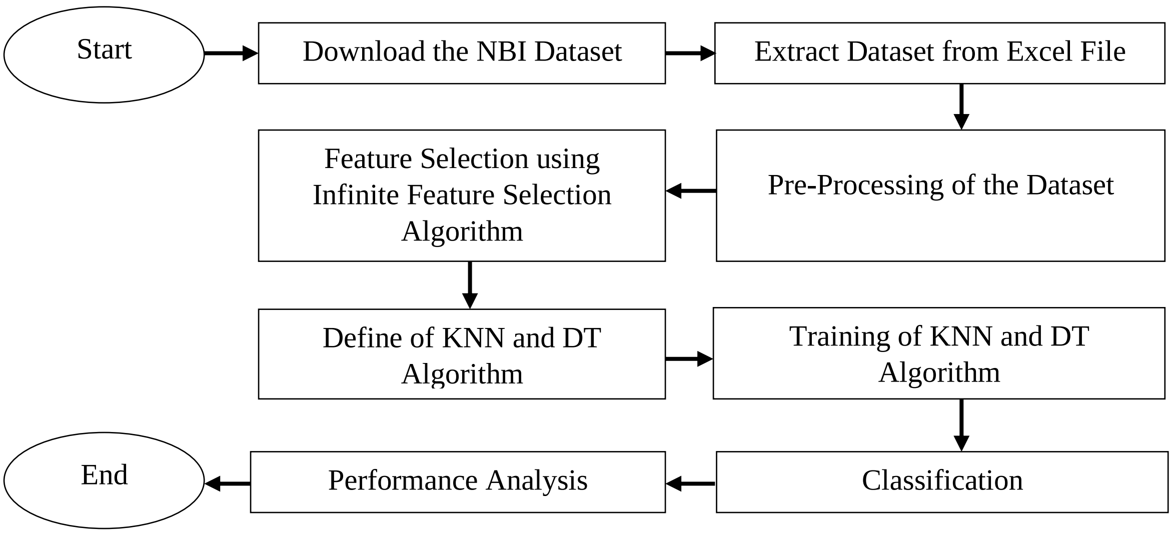

Figure 1 Proposed Model for Bridge Condition Rating

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 [39].
- 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 feature 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, infinite 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 fourth step, the initialization of machine learning algorithm is done for bridge condition rating. The algorithms are taken under consideration are KNN and Decision tree.
- In the fifth step, the training of KNN and Decision tree 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 KNN and Decision tree and combine both output for final prediction.
- In the seventh step, the performance analysis of the proposed model is done using three parameters accuracy factor, mean absolute error, and mean square error. Further, comparative analysis is done with the existing models.

5. Simulation Evaluation

The simulation evaluation of the proposed model is done to validate its performance over the existing models. The setup configuration of the proposed model is explained in Table 1.

Table 1 Setup Configuration

Parameter	Values
Alpha	0.62
Number of Trees	50

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

Table 2 Performance Parameters [40]

Parameter	Equation
Accuracy Factor (AF)	$AF = 10^{1/n} \sum_{i=1}^{n} \mid \log_{10}(\frac{P_i}{O_i}) \mid$
Mean Absolute Error (MAE)	$MAE = \frac{1}{n} \sum_{i=1}^{n} \lvert O_i - P_i \rvert$
Mean Square Error (MSE)	$MSE = \frac{1}{n} \sum_{i=1}^{n} (O_i - P_i)^2$

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 Factor (AF)	1.0685
Mean Absolute Error (MAE)	0.00062696
Mean Square Error (MSE)	0.00062696

5.1 Comparative Analysis

In this section, 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 “artificial neural network (ANN)”, “Markov Model”, “Hidden Markov Model”, and “Semi-Markov Model” [2, 41].

Table 4 shows the comparative analysis based on the accuracy factor parameter. Figure 2 shows the proposed model achieves the lowest accuracy factor value over the other models [2, 42].

Models	Accuracy Factor
ANN	1.3552
Markov Model	2.3312
Hidden Markov Model	1.7521
Semi-Markov Model	2.6763
Proposed Model	1.0685

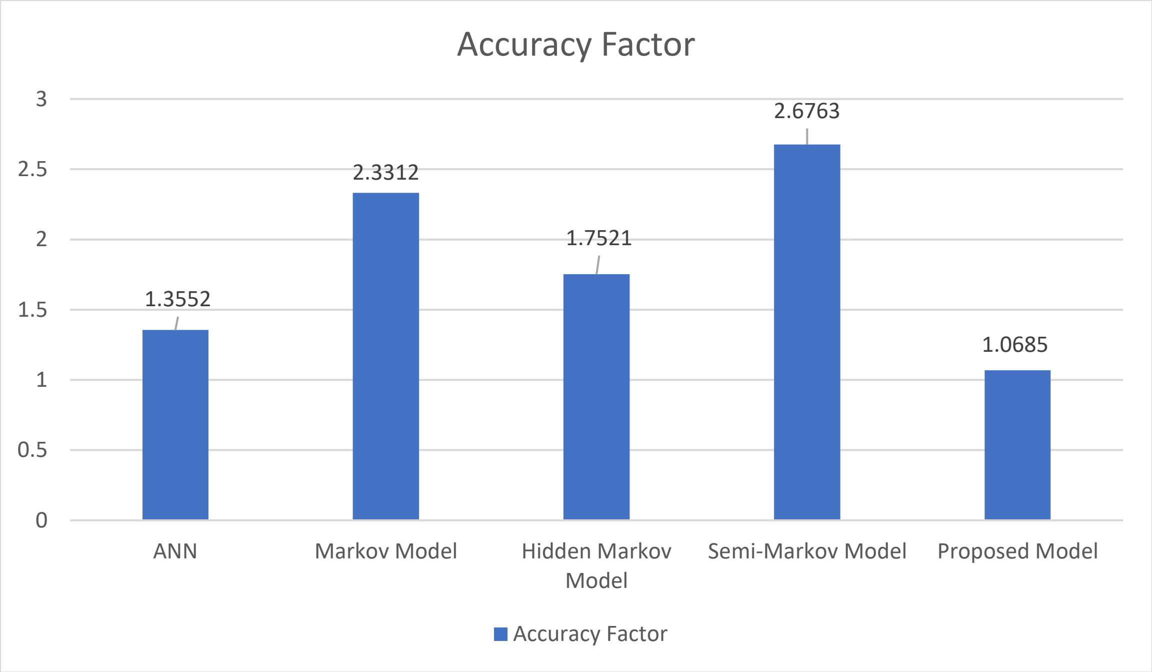

Figure 2 Comparative Analysis based on Accuracy Factor

Table 5 shows the comparative analysis based on the MAE parameter. Figure 3 shows the proposed model achieves the lowest MAE value over the other models [2, 43].

Models	MAE
ANN	0.3154
Markov Model	0.5371
Hidden Markov Model	0.4219
Semi-Markov Model	0.6086
Proposed Model	0.00062696

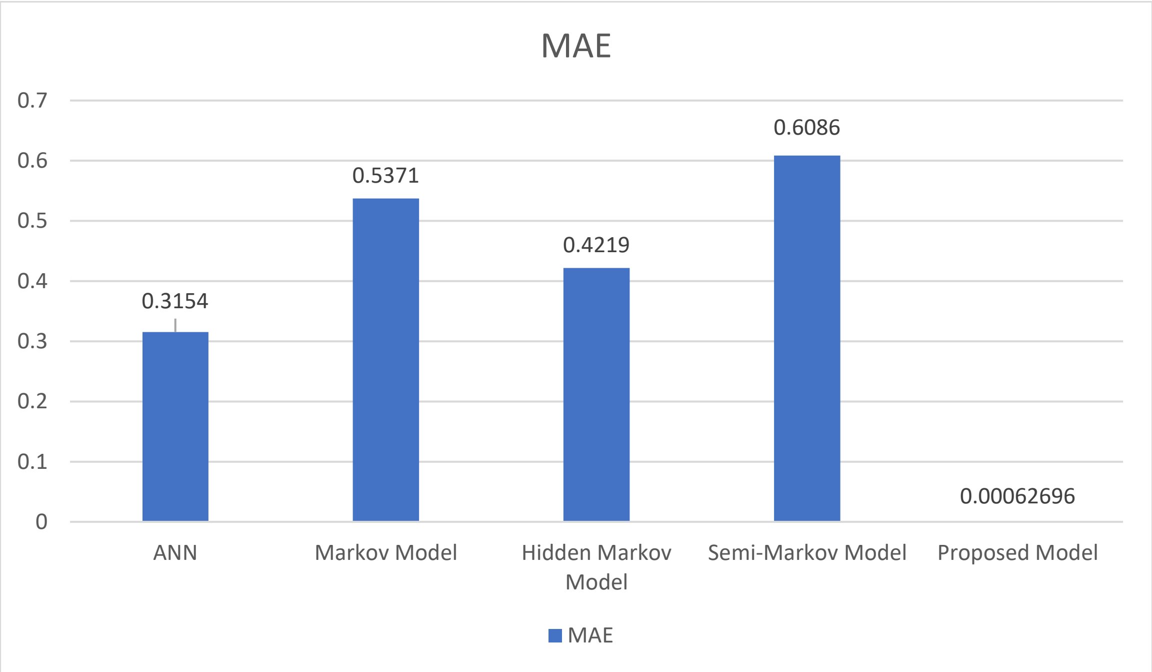

Figure 3 Comparative Analysis based on MAE Parameter

Table 6 shows the comparative analysis based on the MSE parameter. Figure 4 shows the proposed model achieves the lowest MSE value over the other models [2, 44].

Models	MSE
ANN	0.2068
Markov Model	0.3336
Hidden Markov Model	0.3302
Semi-Markov Model	0.4276
Proposed Model	0.00062696

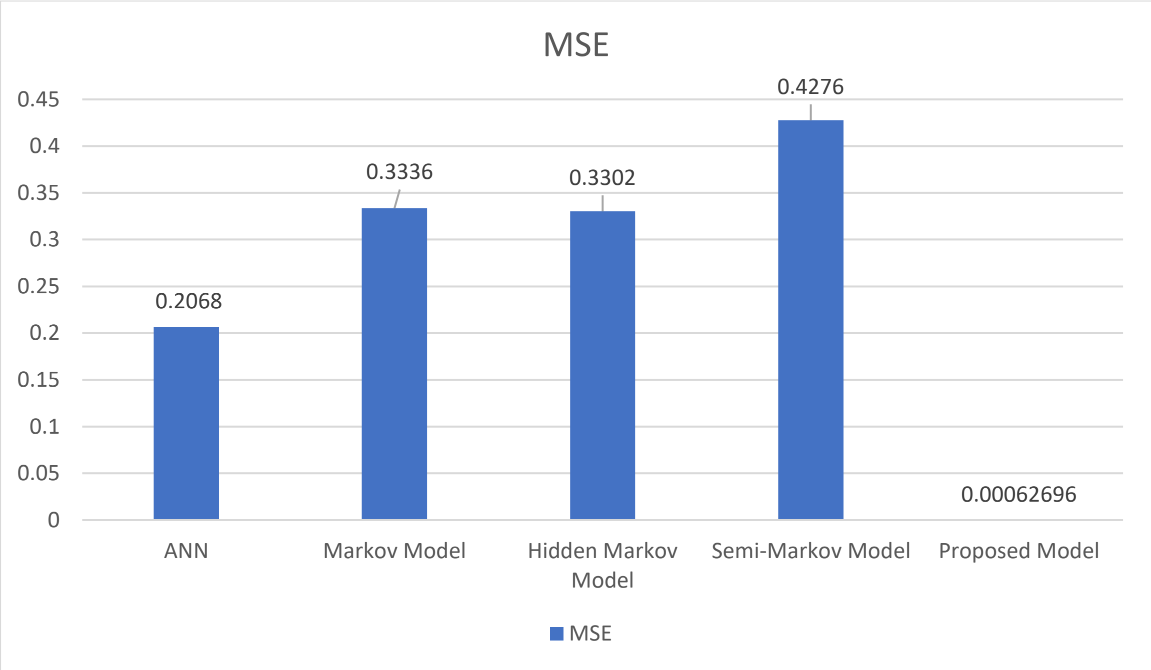

Figure 4 Comparative Analysis based on MSE Parameter

6. Conclusion

We developed a prediction model for bridge condition assessment in this paper. This is accomplished by feature selection and hybridization of machine learning algorithms. The infinite feature selection technique is used to select the most appropriate features of the bridge. Furthermore, the decision tree and KNN machine learning algorithms are being considered for bridge condition evaluation. The simulation is evaluated using a normal NBI database, and three performance metrics are determined: accuracy factor, mean absolute error, and mean square error. The results reveal that the suggested model outperforms existing models [2, 45] such as "artificial neural network (ANN)," "Markov Model," "Hidden Markov Model," and "Semi-Markov Model" in terms of these parameters.

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