Stochastic Modelling of Bridge Condition for Concrete Highway Bridges

Abstract

Highway bridges are an integral part of the built environment. In the recent years, transport and government agencies have recognized the increasing state of bridge deterioration. Routine inspection and evaluation of existing bridges are necessary to ensure that they remain safe for public use. Traditional inspection techniques have several drawbacks, hence, there is a need for accurate future prediction and classification of bridge condition to enable timely intervention and restriction of deterioration in its early phases. This research study proposes to analyze the significance of various factors affecting concrete highway bridge deterioration and condition rating, as well as classify the bridge condition on the basis of the significant parameters. Random forest, a machine learning technique is used in this study to model the bridge data extracted from the archives of the NBI database for the State of Texas in 2019. The results obtained suggested that out of the 40 variables inspected, 12 were insignificant for the prediction of bridge deterioration. RF classification was applied on these 28 significant variables, yielding 99.8% accuracy. Moreover, the AUC obtained from the ROC space yielded 1, indicating excellent performance potential for RF in evaluating the condition of concrete highway bridges.

Keywords: condition monitoring; random forest; machine learning; regression; bridge infrastructure

1 Introduction

Bridges are essential elements of nation's infrastructure, facilitating human travel and enabling transport of goods and services. In the recent years, transport and government agencies have recognized the increasing state of bridge deterioration. There are several intricate and inter-related factors triggering bridge deterioration. These include, but are not limited to, age of structure, deficient design, unfavorable environments, excessive loads, traffic collisions, and maintenance backlog. Additionally, the cost incurred to facilitate rehabilitation is substantial [1,2]. According to the infrastructure report card published by ASCE in 2017, an average of 188 million trips were conducted per day across the 56,000 structurally deficient bridges in the United States [3]. It was also estimated that $123 billion is required to complete the required bridge maintenance and rehabilitation activities. Hence, there is a need for accurate future prediction and classification of bridge condition to enable timely intervention and restriction of deterioration in its early phases.

Conventionally, bridge monitoring and condition rating is carried out by visual inspection, wherein certified professionals conduct routine inspection of bridge elements (including superstructure, substructure, and deck) based on their visual evaluation and simple tools to consolidate data related geometric, physical, and operational state of the infrastructure. The American Association of State Highway and Transportation Officials (AASHTO) and the Federal Highway Administration (FHWA) have specified bridge assessment standards that need to be followed during inspections [4,5]. The results from these inspections are recorded in the National Bridge Inspection (NBI) database which is subsequently utilized to model bridge deterioration and requirements [6]. However, several studies have identified the drawbacks associated with the visual inspection approach. The lack of reliability and substantial variability in condition assessment were two of the concerns raised in [7,8]. As the condition rating implies the maintenance requirements which is turn dictates the capital investment, accurate prediction of the future state of the bridge and its various elements is vital to ensure effective utilization of resources and development of rehabilitation strategy.

This research study proposes to analyze the significance of various factors affecting concrete highway bridge deterioration and condition rating, as well as classify the bridge condition on the basis of the significant parameters. Random forest, a machine learning technique is used in this endeavor to model the bridge data extracted from the archives of the NBI database for the State of Texas in 2019. The findings of this study will enable bridge stakeholders and decision makers to enhance design as well as optimize maintenance and rehabilitation strategies, thereby making efficient use of time and resources. This article is structured as follows: first, a background section summarizing the current literature in this field of work is presented. Secondly, the research methodology detailing the framework of this study is illustrated. Subsequently, consolidation and filtering of the NBI database is described. This is followed by a description of the analysis stages of the collected data, and the documentation and elucidation of the obtained results. Finally, the paper concludes with challenges and limitations facing the classification of future bridge conditions, as well as recommendations for further research and development.

2 Background

Existing literature has described and illustrated numerous approaches for the development of bridge deterioration models as well as for the classification and forecasting of future state of bridge infrastructure. These studies approaches include deterministic, stochastic, and artificial intelligence (AI) models, typically characterized by the variables extracted from bridge management systems or inventory data collected by transportation agencie. Deterministic models statistically analyze the significant relation between established inputs and outcomes [9–11]. Stochastic models, on the other hand, generate more realistic results as well as consider the subjective, multifaceted, and uncertain nature of deterioration models [10,12]. Few studies critically reviewed the current state of literature analyzing bridge deterioration prediction models [13,14]. One such study reported that deterministic model demonstrated better results compared to the commonly used stochastic Markov chain-based model. However, these traditional techniques presented numerous limitations, such as the inability to model random attributes (in case of deterministic) as well as being homogeneous and requiring substantial amount of data for accurate prediction (in case of stochastic). These limitations were observed to be mitigated with the use of ANN, capable of predicting absent condition data arising from irregular inspections.

One such study integrated deterministic and stochastic modelling through Monte Carlo Simulations (MCS) to determine the variability and interdependency of the factors associated with bridge service life modelling [15]. Morcous et al. utilized case-based reasoning to analyze operational factors and generate concrete deterioration models [16]. Another study employed data mining techniques to determine the significance of different parameters resulting in deck decline [17]. Kim and Yoon reported higher durability of concrete bridges compared to steel bridges when integrating multiple regression with geographic information system to determine the significant factors affecting the condition of bridge decks exposed to cold climates [18]. Another study used the Markov process to exploit visual inspection data for condition prediction and maintenance strategy formulization [19]. Moomen et al. modelled deterioration curves for different elements of bridge infrastructure and reported best fit for exponential and polynomial curves [20]. Another interesting study utilized nonlinear regression to reinforce the significance of environmental factors on infrastructure decay and analyze the time available for a bridge deck to deteriorate through different NBI condition ratings in various climatic circumstances [21]. Manafpour et al. employed semi- Markov time-based model to evaluate deterioration transition probabilities and sojourn times [22].

Over the last few years, AI and machine learning techniques have been gaining prominence in structural monitoring and condition assessment. One such study utilized artificial neural network (ANN) to forecast concrete bridge deck condition rating based on the NBI database [23]. The analyzed technique provided optimized solutions for bridge maintenance within the allowed budget. Kim et. al developed an automated prediction model of concrete bridge deck deterioration using regression analyses and data acquired from periodic testing of multiple nondestructive technologies [24]. The model aided in mapping damage progression, assessing condition indices, and the remaining service life of bridge decks. Additionally, the approach was aimed at providing valuable information to stakeholders to enable efficient decision making in bridge management. Another study identified eleven significant factors influencing bridge deck condition deterioration and generated an artificial neural network (ANN) approach for deterioration prediction [25]. The study indicated that maintenance history and age of concrete overlay are important factors affecting deterioration. The proposed model was found to be useful at deterioration pattern classification and maintenance forecasting at both the project level and the network level. A similar study developed an ordinal regression prediction model capable of assessing the influence of bridge attributes on the structural condition and forecast deterioration [26]. The study reported that bridge attributes such as age, current condition, average daily traffic, deck material and area, structural system and material, and length of span are statistically important factors affecting bridge deterioration. The advantage of the proposed method lay in its flexibility in considering users' strategies and risk tolerance. Table 1 highlights some of the previous studies carried out in the field of bridge condition monitoring.

Table 1: Summary of previous studies in the field of bridge condition monitoring

Ref.	Year	Method used	Scope
[23]	2013	Artificial neural network	Forecast concrete bridge deck condition rating and optimize maintenance solutions
[27]	2015	Bayesian belief networks	Deterioration prediction and assessment of maintenance prioritization activities
[28]	2016	Regression	Development of deterioration curves and optimized forecasting based on the planning horizon
[29]	2020	Convolutional neural network	Condition forecasting of bridge components
[15]	2020	Monte carlo simulations	To analyze the interdependency of factors associated with bridge service life modelling

Rafiq et. al utilized dynamic Bayesian belief networks (BBN) to forecast deterioration [27]. The recommended approach was also capable of analyzing 'what-if' scenarios, which was observed to be beneficial for assessment and maintenance prioritization activities. The study highlighted the model's ability to update deterioration prediction utilizing data obtained from inspection, monitoring or maintenance activities. Another study developed an objective, data-based approach for the assessment of prediction capability of regression models for highway bridge component deterioration [28]. The research advocated the utilization of external data evaluation with roll-back data, with the roll-back period encompassing the prediction period for the assessment of short- and long-term forecasting capacity. The proposed approach generated deterioration curves, as well as enables the selection of an optimal forecasting model based on the planning horizon. A similar study proved the usefulness of deep learning models for data-driven condition forecasting of bridge components, including deck, superstructure, and substructure [29]. Convolutional Neural Network (CNN) was utilized particularly for the advantage it possesses over traditional mathematical models' in its ability to characterize high dimensional data abstractions. It was noted that the forecasted bridge condition may be history reliant, which is subject to further research.

Martinez et. al analyzed various classification models, including k-nearest neighbors (k-NN), decision trees (DTs), linear regression (LR), ANN, and deep learning neural networks (DLN), to forecast bridge condition index (BCI) [30]. The results obtained from performance measure comparison and statistical validation indicated that the investigated models were capable of predicting BCI accurately, with relative error less than 1%. However, the study recommended utilizing DTs particularly due to its reliability and accuracy in critical value ranges. Another study integrated data mining models, namely, Kohonen neural network and long short-term memory (LSTM) neural network [31]. The former was observed to be efficient at obtaining classification pattern and outlier detection, whereas the latter was proficient at forecasting defection values. The evolving trend of the bridge infrastructure was attained by contrasting the predicted value with its limit value. Assaad et. al compared the feasibility of machine learning techniques, ANN and kNN, for the development of a data-driven bridge management system including damage prediction [32]. Accuracy of the techniques was improved by finding the optimal set of hyper-parameters. The study reported ANN algorithm as demonstrating higher performance compared to its counterpart and suggested the utilization of the proposed framework as a complementary technique to noninvasive methods.

3 Methodology

The primary objective of this study is to examine and determine the significance of explanatory factors obtained from the NBI inspectional archives to forecast and classify the overall condition rating of concrete highway bridge infrastructure. The bridge data extracted in this study is categorized according to the level of service and functional class. The significance of the geometric, inventory and operational factors affecting the bridge condition was analyzed using a deterministic approach, linear regression. Subsequently, machine learning techniques, particularly Random Forest are applied to classify the bridge condition rating based on the explanatory variables. The methodology followed is described illustratively in figure 1, and can be summarized in the following 6 steps:

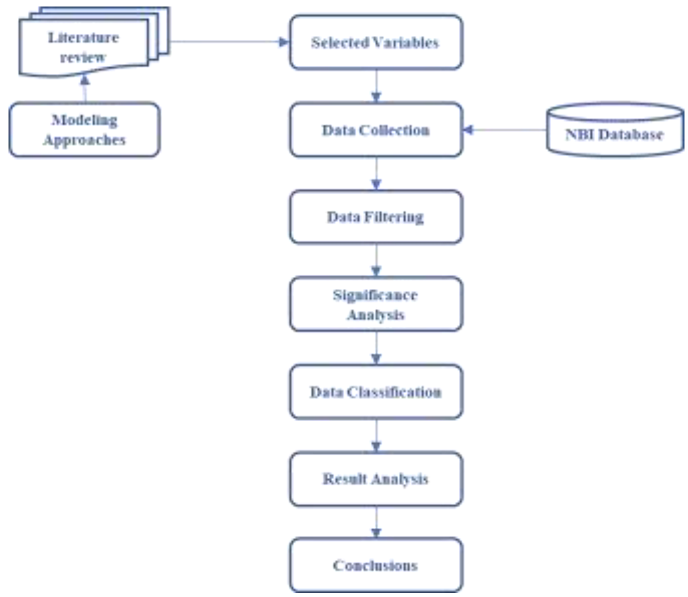

Figure 1: Research Methodology

- Literature review: details the current state of literature in bridge condition monitoring and deterioration modelling;
- Data collection and filtering;
- Statistical analysis of significant variables affecting the concrete highway bridge condition employing linear regression;
- Machine learning based classification analysis using Random Forest classifier;
- Results analysis; and
- Conclusion and recommendation for future studies.

4 Data Collection and Filtering

The inception and continuation of NBI was authorized by the Federal-Aid Highway Act of 1968. This was followed by the publication of the "Recording and Coding Guide for the Structural Inventory and Appraisal of the Nation's Bridges" by FHWA which describes the documentation of data elements that would comprise the NBI. This database functions as an archival record, logging information from more than 600,000 bridges in the 50 states. Several researchers have exploited the data contained in this record as a major consistent data source [6,33–35]. The bridge structural condition and deterioration can be developed by exploiting the inventory, geometric, operational, and inspection information archived in the NBI database as well as by analyzing the relative importance of these variables against bridge condition rating. The NBI database indicates the overall bridge rating derived from the condition ratings of the individual bridge elements including superstructure, substructure, and deck. The bridge elements are rated as integers between 0 to 9, 0 denoting failed condition whereas 9 denotes excellent condition. The inspection and rating are conducted for the entire element, including the surface, sides, and bottom. Table 2 details the general rating guidelines allotted for the various bridge elements, extracted from the coding guide published by U.S. Department of Transportation (USDOT) and FHWA [36]. Such an overall elemental rating feeds into the three general bridge condition categories, namely good, fair, and poor condition, which will be utilized as the prediction output in this research. According to the NBI guidelines, bridges are classified to be in *good condition* if the overall condition rating is between 7 to 9. Such bridges only require routine maintenance. On the other hand, preventive maintenance or minor rehabilitation may be prescribed for those bridges receiving overall condition rating of 5 to 6, classed as *fair condition*. However, major rehabilitation, replacement, temporary or even permanent closure may be proposed for those bridges rated 0 to 4 and classified as poor condition.

Table 2: NBI Condition Rating Guidelines [36]

Code	Description
N	Not Applicable
9	Excellent Condition
8	Very Good Condition
7	Good Condition
6	Satisfactory Condition
5	Fair Condition
4	Poor Condition
3	Serious Condition
2	Critical Condition
1	Imminent Failure Condition
0	Failed Condition

The USDOT has recorded the inspection results of more than 54,000 bridges in the state of Texas. In this study, the total set of Texan bridges were filtered to generate a subset having particular characteristics. This was accomplished by excluding those bridges with elemental condition rating of N: Not Applicable as well as those for which the condition rating was absent. Moreover, only those bridges classified as concrete and prestressed concrete highway bridges with mainline designated level of service, and urban and rural principal arterial functional classification are included in the analysis. The independent variables before refinement include minimum vertical clearance, tolls, age, traffic lanes on and under the structure, average daily traffic, design load, approach roadway width, degrees skew, bridge railings, transitions, approach guardrail, type of service on and under bridge, number of spans in main unit, number of approach spans, total horizontal clearance, length of maximum span, structure length, curb or sidewalk widths, bridge roadway width, deck width, minimum vertical clearance over bridge roadway, minimum vertical underclearance, minimum lateral underclearance, minimum lateral underclearance, deck, superstructure, and substructure, direction of traffic, deck structure type, wearing surface/protective system, percentage of average daily truck traffic, deck area. On the other hand, the dependent variable being predicted is bridge condition. Detailed descriptions of these variables are available in the Recording and Coding Guide for the Structure Inventory and Appraisal of the Nation's Bridges [36].

5 Model Development

5.1 Regression Model

National Bridge Inspection Standards necessitate the documentation of over 100 parameters, not all of which may be pertinent for the development of a bridge condition classification model [4]. Hence, linear regression was initiated to investigate the significant factors and identify the best subset of variables to attain the highest coefficient of determination (R^2). This data refinement process was carried out using IBM SPSS Modeler, a graphical and predictive analytics software.

5.2 Classification Model

The refined dataset, consisting of approximately 6,700 highway bridges, obtained after the significance analysis using the regression model, are further examined using MATLAB, a computing and design platform. Random Forest (RF), a supervised machine learning classification technique, which functions by generating large clusters of decision trees (DT). RF integrates feature selection and bagging methods, unlike conventional DT which utilizes all variables to develop a tree-like graph. A subset of one or more strong contributing factors of the prediction parameter is formed to generate the tree-like classification diagram, recognized as the bootstrap sample. The inherent bagging process groups the models with the generates bootstrapped samples by voting. RF demonstrates improved stability and accuracy, curtails overfitting, and lowers variance.

6 Results

6.1 Feature Selection

The results obtained after linear regression suggested that out of the 40 variables inspected, 12 were insignificant for the prediction of bridge deterioration. These included approaching roadway width, bridge skew angle, service type on the bridge (highway or pedestrian), number of spans in the approach spans to the major bridge, length of maximum span, bridge roadway width, deck width, minimum lateral underclearance, deck structure type, surface type, and area. This is validated based on existing research which identified similar significant variables [37]. Hence, the refined list of significant variables to be further utilized in the study is illustrated in Table 3. It is to be noted that some of the factors such as age was calculated from the year of building the bridge, available in the NBI data. The primary significant factors were observed to be deck condition, age, and inspection frequency.

Table 3: List of significant variables obtained after regression

Variable Name	Description	Type
Toll	Toll status of the structure	Nominal
Age*	Age of the structure at inspection	Numeric
Traffic Lanes On/Under	Number of lanes carrying traffic on/under the structure	Numeric
Average Daily Traffic	The average daily traffic volume for the route	Numeric
Railings	The condition of the bridge railings	Nominal
Approach Guardrail	The condition of the bridge railings	Nominal
Approach Guardrail Ends	The condition of the bridge railings	Nominal
Type of Service	The type of service "under" the bridge	Nominal
Approach Kind	The kind of material of the approach spans	Nominal
Approach Type	The type of structure of the approach spans	Nominal
Main Unit Spans	The number of spans in the main unit	Numeric
Total Horizontal Clearance	The total horizontal clearance of the structure	Numeric
Structure Length	The length of the structure	Numeric
Curb or Sidewalk Widths	The widths of the left and right curbs or sidewalks	Numeric
Minimum Vertical Clearance	The minimum vertical clearance over roadway/beneath the structure	Numeric
Deck Condition*	The overall condition rating of the deck	Ordinal
Superstructure Condition	The overall condition rating of the superstructure	Ordinal
Substructure Condition	The overall condition rating of the substructure	Ordinal
Operating Rating	Maximum permissible load level the structure may be subjected to	Numeric
Inventory Rating	Load level that can utilize the structure for an indefinite period of time	Numeric
Inspection Frequency*	Number of months between designated inspections of the structure	Numeric
Traffic Direction	Direction of traffic of the inventory route	Nominal
Membrane Type	Type of membrane surface on the bridge deck	Nominal
Deck Protection	Type of protective system of the bridge deck	Nominal
Percent ADT Truck	Composition of truck traffic using the bridge	Numeric
Bridge Condition	The prescribed bridge rating that will decide the maintenance action	Ordinal

* Most significant factors

The model generated from linear regression resulted in a satisfying adjusted R^2 value (0.891). Figure 2 illustrates the normal probability distribution plot of the residuals arising from the generated model. Evidently, majority of the residuals adhere to the straight-line path, with a few scattered outliers.

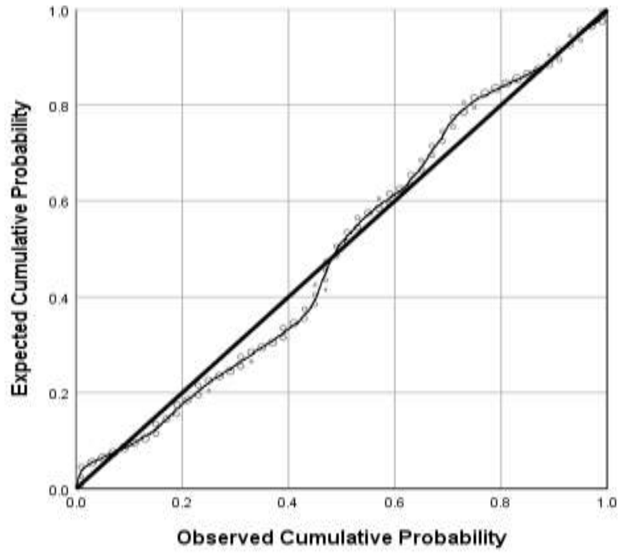

Figure 2: Normal P-P plot of regression standardized residual

6.2 Bridge Condition Prediction

As mentioned previously, the predictive model for the classification of bridge condition, based on the inventory and operational data, is obtained by applying the RF algorithm. The time required to train the model was 13.8s at a prediction speed of approximately 19000 obs/s. The prediction efficiency can be verified based on the following performance indicators, namely, accuracy, confusion matrix, and receiver operating characteristic curve (ROC curve). Accuracy is the proximity of the forecasted value to the target value. Using RF method, the model was trained with an accuracy of 99.8%, which is satisfactory. The confusion matrix visualizes the prediction performance, generated subsequent to the analytical results including true positives (TP), true negatives (TN), false positives (FP) and false negatives (FN). TP and TN represent those instances when the model accurately classifies the output, whereas FP and FN represent incorrect classification of the outputs. Figure 3 illustrates the confusion matrix obtained after applying the RF method to the dataset. It can be observed that accurate classification was obtained for highway bridges rated “good” and “fair”. However, only 51.5% of those bridges rated as “poor” was classified correctly. This may be attributed to the fact that only 33 bridges out of the 6700 data points were rated as poor which may not be sufficient for accurate classification.

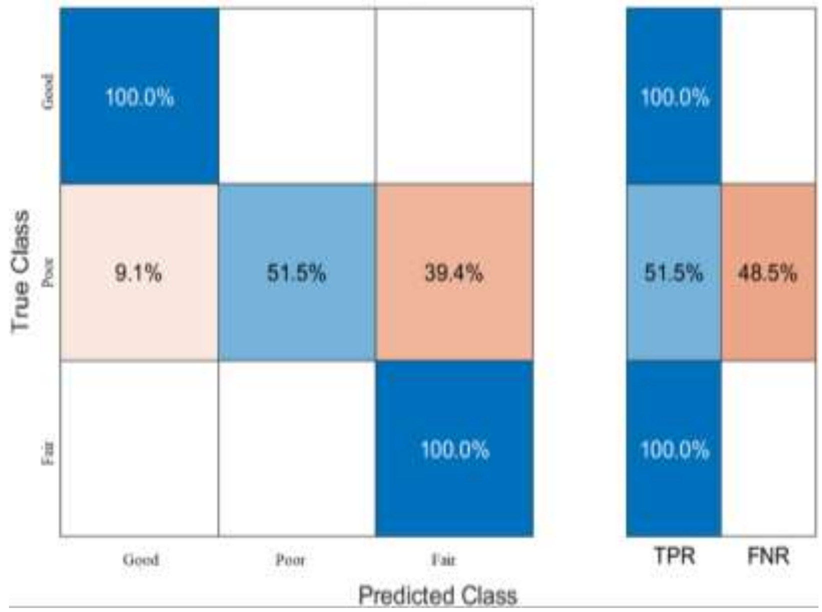

Figure 3: Confusion matrix of the proposed model

The ROC curve and the area under the curve (AUC) represents the diagnostic capability of the utilized classifier. The ROC curve plots the probability curve of true positive rate (TPR) and false positive rate (FPR), at different setting parameters. A model that has excellent prediction capabilities would return AUC close to 1, generating a point at the upper left area of the ROC space, indicating the absence of FN and FP. Figure 4 illustrates the ROC curve and AUC obtained after applying the RF classifier. It can be observed that the prediction capability of the generated model is high based on the AUC value which is equal to 1. Moreover, those bridges rated “good” and “fair” generated a point at the upper left corner of the ROC space indicating good classification, whereas those rated “poor” yielded the point at the mid left side of the ROC space, indicating subpar classification. These results corroborate with the findings obtained from the confusion matrix.

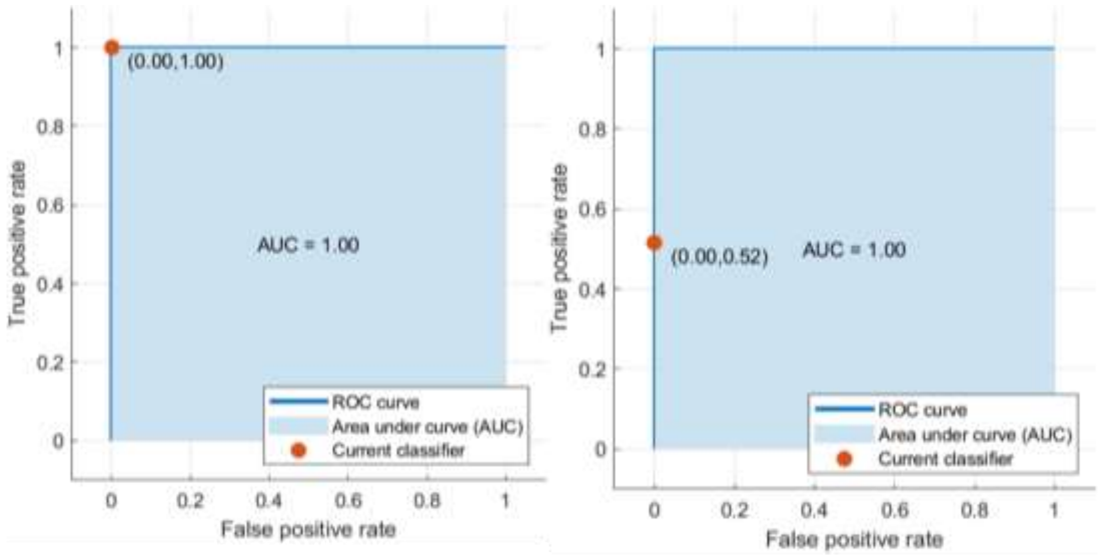

Figure 4: ROC Curve of the proposed method

7 Conclusions and Recommendations

Highway bridges are an integral part of the built environment. Routine inspection and evaluation of existing bridges are necessary to ensure that they remain safe for public use. Current inspection practices, particularly visual inspection, are time- consuming, lack reliability and demonstrate substantial variability. Hence, accurate prediction of the future state of the bridge and its various elements is vital to ensure effective utilization of resources and development of rehabilitation strategy. This paper proposes the utilization of machine learning technique, namely random forest, for the prediction and classification of future bridge condition. Prior to that, the significance of various factors affecting highway bridge condition is evaluated using linear regression. The NBI database compiled for the State of Texas in 2019 is exploited for this endeavor.

The results obtained suggested that out of the 40 variables inspected, 12 were insignificant for the prediction of bridge deterioration. RF classification was applied on these 28 significant variables, yielding 99.8% accuracy. Moreover, the AUC obtained from the ROC space yielded 1, indicating excellent performance potential for RF in evaluating the condition of concrete highway bridges. The findings of this study will enable bridge stakeholders and decision makers to enhance design as well as optimize maintenance and rehabilitation strategies, thereby making efficient use of time and resources. Further studies will be conducted to evaluate the model performance in case of steel bridges. Additionally, other research avenues include comparison of RF technique with other machine learning models.

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