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An Improved Inspection Process and Machine-Learning-Assisted Bridge Condition Prediction Model

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Abstract: Bridges have a special place in transportation infrastructures and road networks due to their direct relationship with other places. These structures have the purpose of maintaining the traffic loads of the highway, crossing any obstacle, and performing effective communication between two destinations. Costs associated with bridge maintenance continue to be expensive due to their widespread use and stringent inspection requirements. Many researchers have been working on methods to use machine-learning (ML) techniques to forecast specific situations rather than physically checking bridges as part of the maintenance process in recent years. The practical value of the models has, however, been severely constrained by issues such relatively poor model evaluation results, unstable model performances, and the ambiguous application of established models in real-world scenarios. This work showed a thorough method of bridge condition prediction model building from feature engineering to model evaluation, along with a clear procedure of applying the produced model to actual usage, using data from the United States National Bridge Inventory (NBI) and the Adaboost algorithm. Multiple ML model assessment metrics' findings revealed that the given model outperformed the majority of earlier studies in terms of values and stability. The case study demonstrated that there is a 30% reduction in the number of bridges that need to be inspected. This study serves as a crucial resource for the practical application of ML approaches in the forecast of the status of civil infrastructure. Additionally, it shows that boosted ML models may be a superior option as modeling algorithms advance. To explore the main influencing aspects of bridge conditions, a predictor importance analysis is also offered.

Keywords: bridge condition prediction; automated inspection; infrastructure maintenance; machine learning; AdaBoost

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1. Introduction

According to the national bridge inventory of the Federal Highway Administration (FHWA) in the USA, there are currently 620,669 bridges across the country [1]. However, as their infrastructure assets age and maintenance funding becomes increasingly scarce, many state departments of transportation (DOTs) are confronted with previously unheard-of difficulties. Consequently, using ML algorithms to forecast their circumstances and facilitate management is gaining more and more attention [2]. The year-round upkeep of bridges takes a lot of time and costs a lot in manpower and equipment. Additionally, in order to gather information about the bridge's state prior to each maintenance task, skilled professionals frequently need to undertake on-site visual inspections of the structure. These inspections take a lot of time and labor hours as well. If bridges are not adequately managed and maintained, the general public's safety will suffer greatly [3].

Predictive ML models have received a lot of interest recently in a variety of fields, including cyber security [4], psychology [5], finance [6], and civil infrastructures [7,8]. Similar research has been conducted on bridges in an effort to anticipate their overall state or the status of specific components, which will help with maintenance [9,10]. However, issues like inconsistent model performances, low model evaluation results, and the ambiguous application of developed models in real-world scenarios have significantly reduced the usefulness of the models.

Usually, a rating system is used to compare the condition of the bridge's various parts to determine how much they have degraded. The components are then given a condition rating [11–13]. This rating information along with the bridge's physical and usage information like length, roadway width, kind of material, age, and average daily traffic (ADT) are stored in the Bridge Management System's (BMS) database. Among the many different ratings of a bridge [14,15], bridge deck condition and structure-related conditions are the most important, because they directly determine the safety and serviceability of the bridge [10,15,16]. In addition, once the bridge deck and structure of the bridge are damaged, it will lead to more serious displacement, deformation, or damage of the bridge during service [17].

In order to anticipate bridge condition states and improve the current bridge management process, an AdaBoost artificial neural network (ANN) model was proposed in this research. This model aims to decrease the number of bridges that need to be examined. The suggested model's input variables were prepared, extracted, and determined using a feature engineering approach [18].

Along the path of completing this research, the following tasks were completed:

1. A literature review was carried out to determine the application of current machine-learning algorithms in the field of bridge condition prediction, determine the selection of input variables and output, selection of the model evaluation metrics to judge the performance ability of the model, and an overview of the used data in this study.
2. Feature engineering processing was performed on Texas bridge inventory data to prepare, extract, and determine representative features from the original database and provide more effective solutions.
3. The AdaBoost model was established with the data processed by feature engineering and select corresponding model evaluation metrics.
4. A case study was provided, and the results show that the use of the proposed model will reduce the number of bridge inspections by about 29.73%.

2. Literature Review

The literature review covers the following areas: (1) Machine-learning (ML) applications in bridge condition prediction; (2) Input and output variable selection; (3) Machine-learning model evaluation metrics; (4) Data overview and the AdaBoost algorithm.

2.1. Machine-Learning Applications in Bridge Condition Prediction

Machine-learning algorithms are being used more and more in the management process to help with resource allocation, increase the effectiveness and caliber of bridge maintenance work, and achieve preventive effects [19–22]. For bridges, related applications in structural condition prediction are mainly conducted in the following ways [9,10,23]: (1) A forecasting model that predicts future bridge deterioration conditions based on the bridge characteristics [24]; (2) Deterministic curve models [25], which mainly include curve fitting methods, regression analysis curve prediction models, and time series methods; (3) Stochastic models [26], mainly including the Markov chain method [27] and reliability theory; (4) Artificial intelligence models [28,29], which mainly use artificial neural network (ANN) algorithms [30,31]; (5) SHM models based on visual inspection, image recognition, or real-time data collection and analysis. For example, Fang et al. reported the prediction of web-residual strength of cold-formed stainless steel channel sections under end double-flange loading conditions using a deep confidence network (DBN) [32]; Philip et al.

used convolutional neural networks (CNN) to accurately identify and classify structural cracks and security [33]; Cardellicchio et al. used different machine-learning methods to automatically identify defects in existing reinforced concrete (RC) bridges, opening up new scenarios for road management companies and public organizations to assess the health of road networks [34]. The main advantages of these applications include reduced labor needs, fast data collection, and accurate knowledge of the bridges' conditions without interference to the daily operation of structures [21,35]. However, there are still few studies using more recent machine-learning techniques like boosted algorithms to create more accurate and reliable bridge structural state prediction models [17,36,37].

2.2. Input and Output Variable Selection

Similar decisions regarding input variables have been made in earlier research on utilizing machine-learning algorithms to anticipate bridge conditions [2,16,28,38]. Data accessibility and the scope of the research are the key constraints on the selection process. Age, design load, wear surface type, material and/or design type, structure length, and ADT are a few of the variables that are most frequently used. Table 1 below lists the input variables used in the proposed study versus previous studies.

Table 1. Used input variables in existing studies.

Input Variable	This Study	Existing Study									
Time		2008	2013	2015	2016	2019	2019	2020	2020	2021	2022
Author		Lee	Creary	Huang	Shan	Ali	Lim	Liu	Allah	Alogdianakis, et al.	Hussaini
Type of wearing surface	√	√				√		√	√	√	√
Type of design and/or construction	√	√	√	√		√	√	√	√	√	√
Deck structure type	√	√	√			√	√	√	√	√	
Length of maximum span	√				√			√		√	
Design load	√	√	√	√	√				√	√	√
Age	√	√	√	√	√	√	√	√	√	√	√
Kind of material and/or design	√	√	√	√	√	√	√	√	√	√	
Lanes on and under the structure	√				√	√		√			
Functional classification of inventory route	√							√			
Inventory route, total horizontal clearance	√										√
Deck width, out-to-out	√				√	√				√	√
Maintenance responsibility	√							√			
Inventory route	√										
Deck protection	√	√				√		√	√	√	
Type of service under bridge	√										
Minimum vertical under clearance	√										
Structural length	√		√	√	√	√	√	√	√	√	√
ADT	√	√	√		√	√	√	√		√	√
Type of membrane	√	√				√		√	√	√	
ADTT	√	√	√		√	√	√	√		√	√

Similar circumstances apply to output variables, which are primarily chosen by researchers depending on their research objectives and the availability of relevant data. In earlier studies, certain authors just used the overall structure as the output variable to create a predictive model, while others chose the output variables for the bridge deck, superstructure, and substructure.

For the bridge deck condition, Lim [10] stated that the bridge deck directly supports the load on the bridge, which directly determines the safety and usability of the bridge; Shan [39] and Huang [40] determined the deterioration of the bridge superstructure and substructure. In the study of Hussaini [35], it was pointed out that the damage to the bridge structure will damage the stability and bearing capacity of the bridge, and even lead to the collapse of the bridge and cause safety accidents.

Following a thorough review of the literature, it was found that each of the four aforementioned conditions is directly related to the bridge's carrying capacity and general stability, and that any one of them could have a significant effect on traffic flow and safety.

2.3. Machine-Learning Model Evaluation Metrics

Choosing suitable evaluation metrics is a key step in properly assessing the performance of machine-learning models [41,42]. In existing studies, model accuracy is commonly used to assess the performance of models [43–45]. However, studies have shown that in many classification applications, the performance of ML models cannot be fully evaluated based on accuracy alone [46]. Therefore, in this study, the evaluation metrics used are the accuracy, precision, recall, F-score, and area under the ROC curve for more comprehensive model evaluations, and their advantages are as follows [47–49]:

Accuracy is the number of correct predictions divided by the total number of predictions. Despite the widespread usability, accuracy is not the most appropriate performance metric in some situations, especially in the cases where target variable classes in the dataset are unbalanced. Precision is the number of true positives divided by the total number of predicted positives. Recall measures the model's ability to identify all instances of the target class. In general, there is a trade-off between recall and precision. For example, in situations where it is preferred to detect instances of a minority class, recall is more important than precision. As in the context of fraud detection, it is usually more costly to miss a positive instance than to falsely label a negative instance. F-score is the harmonic mean of precision and recall and is used to measure the overall performance of a model. The receiver operating characteristic (ROC) curve is a graphical representation of the performance of a binary classification model. It plots the true positive rate against the false positive rate at different thresholds. The fewer errors, the further the ROC curve moves up and to the left. Therefore, the better the classifier works, the higher AUC will rise.

2.4. Data Overview and AdaBoost Algorithm

The National Bridge Inventory (NBI) of the United States Federal Highway Administration (FHWA) provided the data for this study [1]. Various bridge information is available yearly according to the NBI's Coding Guide. For managing the more than 600,000 bridges in the United States, the NBI offers significant and comprehensive information.

Previous studies using the NBI database for bridge prediction have used more input variables, but this increased cost and complexity reduced efficiency. Additionally, different databases and research directions have led to different data selection criteria [10,17].

Considering the complexity of different components of bridges, there are multiple influencing factors in their degradation process. In this paper, the input and output variables required for the proposed study are screened out by means of feature engineering and literature review. Table 2 shows the output variables used by each model and the corresponding amount of bridge data. Compared to the existing studies and the data volume requirements of AdaBoost, the number of bridges under the conditions of these four ratings is considered sufficient [15,41,50,51].

Table 2. The amount of model data.

Rating	Number of Bridges
Superstructure	34,764
Substructure	34,764
Structural	55,476
Deck	34,897

AdaBoost is an ensemble learning method which was initially created to increase the efficiency of binary classifiers. AdaBoost uses an iterative approach to learn from the mistakes of weak classifiers and turn them into strong ones. The core idea is to train different subtypes (weak classifiers) for the same training set and combine these trained subtypes to form a stronger classifier (strong classifier) [52].

The flowchart of AdaBoost is shown in Figure 1.

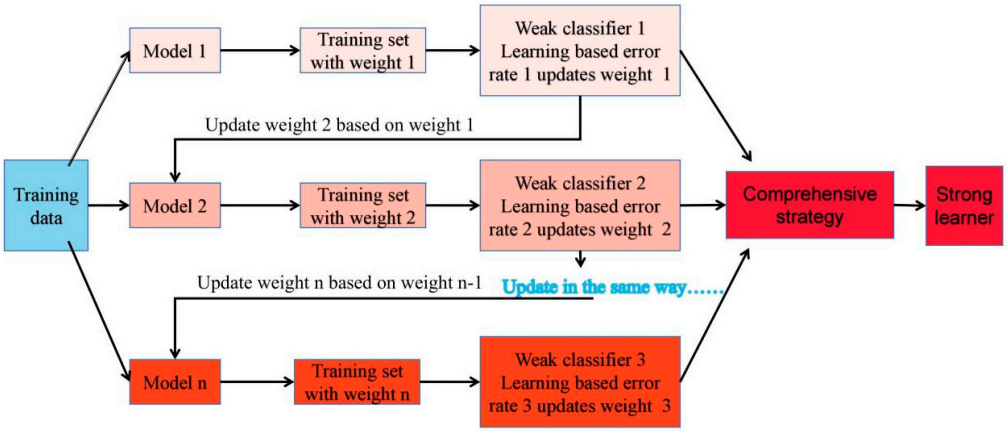


Figure 1. AdaBoost algorithm step-by-step illustration.

3. Methodology

This paper first applied a feature engineering technique to the initial NBI data in accordance with the completed literature analysis and background investigation. The input variable is chosen, and the original 10-point ratings are transformed into binary classes, each of which reflects a distinct state of the bridge. After that, the prediction models were created using the AdaBoost ANN algorithm. Figure 2 depicts the primary steps taken in this investigation.

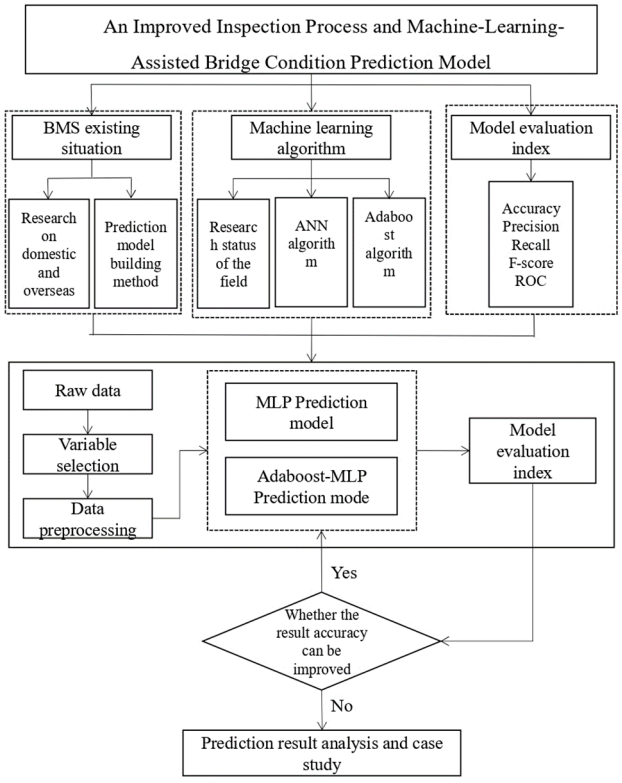


Figure 2. Flowchart of the research.

3.1. Feature Engineering of the Original NBI Data

For machine-learning models to be developed properly, feature engineering is crucial. It is necessary to refine the expression of features for usage as input into machine-learning algorithms and process the raw data to obtain usable features [25]. Typically, feature

engineering entails steps like variable transformation, dimensionality reduction, feature extraction, and feature selection [50].

Since there are many missing values and information that is not specifically related to the status of the bridges, the data in the NBI are not originally appropriate for machine-learning applications. Therefore, based on the conducted literature review and the data availability in the inventory, 20 input variables were selected for developing the proposed AdaBoost model of this study as shown in Table 3 [52]. It should be noted that the age information was derived using the construction time, most recent re-built time, and the current year information because it was not directly available in the inventory.

Table 3. Input variable name and definition.

Name	Definition
Design load	The ultimate load on the structure
Age	Age of the bridge
Kind of material and/or design	The main material of the bridge
Functional classification of inventory route	Located in the city or countryside
Type of design and/or construction	The design structure of the bridge
Deck structure type	The type of deck system on the bridge
Length of maximum span	Maximum span length of the bridge
Type of wearing surface	Information on the wearing surface of the bridge
Maintenance responsibility	The body responsible for repairs
Inventory route, total horizontal clearance	Horizontal distance of bridges
Deck width, out-to-out	The width of the bridge
Inventory route	Bridge basic information
Type of service under bridge	Type of traffic under the bridge
Lanes on and under the structure	The number of carriages for the structure
Deck protection	Material of deck protection
ADTT	Average daily truck traffic
ADT	Average daily traffic
Minimum vertical under clearance	Minimum passage height
Structural length	Bridge structure length
Type of membrane	Type of membrane material

3.2. Output Variable Selection and Data Re-Classification

As stated in the literature review section, four condition ratings were used as the output variable since they impact the overall structural stability of a bridge the most, which includes superstructure condition, substructure condition, deck condition, and structural evaluation.

The original rating information was displayed on a 10-point scale, with 0 denoting total failure and 9 denoting brand-new circumstances. In this study, ratings from 0 to 6 into one class and ratings from 7 to 9 into another were reclassified using a binary system. This reclassification was performed mostly due to the fact that Rating 6 is an important rating that is frequently used to evaluate whether an on-site inspection of a bridge is necessary. Additionally, binary classification is superior to multipoint classification in the following ways:

(1) The dichotomous model is simpler to comprehend and use, and its structure is simple and straightforward to study and interpret;
(2) The binary-classification approach performs extremely well when processing massive amounts of data, which not only conserves computing power but also increases computing accuracy and efficiency;
(3) The binary-classification model may handle centralized or unbalanced data sets by modifying the threshold and establishing the loss function.

The definitions of the selected output variables are shown in Table 4.

Table 4. Output variable name and definition.

Model Output Variables	Definition
Superstructure condition	A structure integrated with the superstructure
Substructure condition	Considered as the portion below the superstructure
Structural evaluation	Evaluation of the overall structure of the bridge
Deck condition	A bridge deck integrated with the superstructure

3.3. AdaBoost Bridge Condition Prediction Model Development

As previously mentioned, 20 input variables and 4 output variables were chosen once the data preprocessing was finished to build the bridge condition prediction model [53]. IBM's SPSS Modeler 18.0 data mining software was utilized to create the model [54]. The assignment of types and roles to the variables utilized is the first step in the model creation process. Second, the number of hidden layers and the type of activation function are the two most crucial adjustable factors for ANN models [41]. An activation function node in a neural network transforms input data into output data. Both the multilayer perceptron (MLP) and the radial basis function (RBF) are activation functions that can be used in SPSS Modeler. MLP with one hidden layer was applied in this investigation. Finally, the data were divided into a training set (70%) and a test set (30%) using the cross-validation approach. Table 5 displays the primary ANN model establishment parameters, while Figure 3 displays the model created using SPSS.

Table 5. Model main parameters.

Target	Build the AdaBoost Model
Activation function	MLP
Hide layer	1
Use the maximum training time	Ture
Customize the maximum training cycle	False
Use minimum accuracy	False
The number of component models for boosting	10
Random seeds	229,176,228
The predictor is missing a value	Columnar deletion

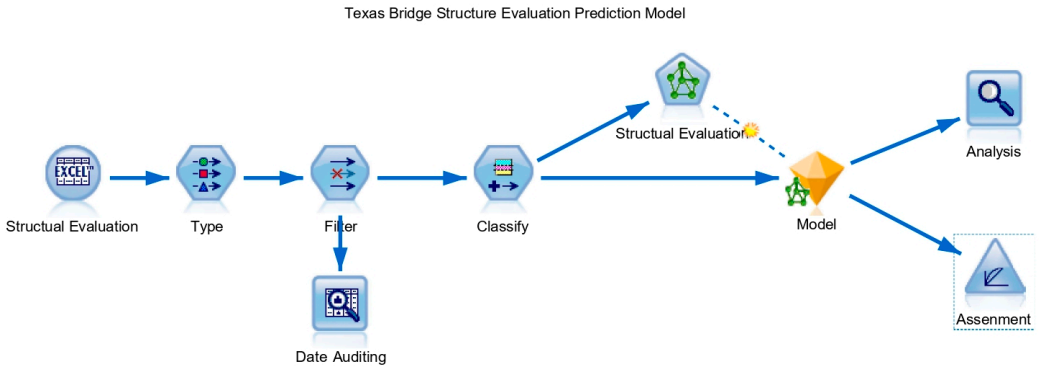


Figure 3. Bridge structure evaluation prediction model.

4. Results

4.1. Model Evaluation Results

As explained in the literature review section, using a single evaluation metric will cause significant bias to the performance evaluations of machine-learning algorithms. Thus, in this study, accuracy, precision, recall, F-Score, and AUC under ROC are used, and the results are as shown in Table 6 and Figure 4.

Table 6. AdaBoost-ANN model results.

Rating	Dataset	Accuracy	Precision	Recall	F-Score	AUC
Superstructure	Training	82.07%	0.86	0.88	0.87	0.89
	Testing	82.66%	0.86	0.89	0.88	0.89
Substructure	Training	78.32%	0.81	0.84	0.82	0.86
	Testing	77.62%	0.80	0.82	0.81	0.86
Structural	Training	89.02%	0.84	0.82	0.83	0.95
	Testing	88.57%	0.83	0.82	0.82	0.95
Deck	Training	80.25%	0.84	0.90	0.87	0.85
	Testing	80.59%	0.84	0.91	0.87	0.86
Average	Training	82.42%	0.84	0.86	0.85	0.89
	Testing	82.36%	0.83	0.86	0.85	0.89

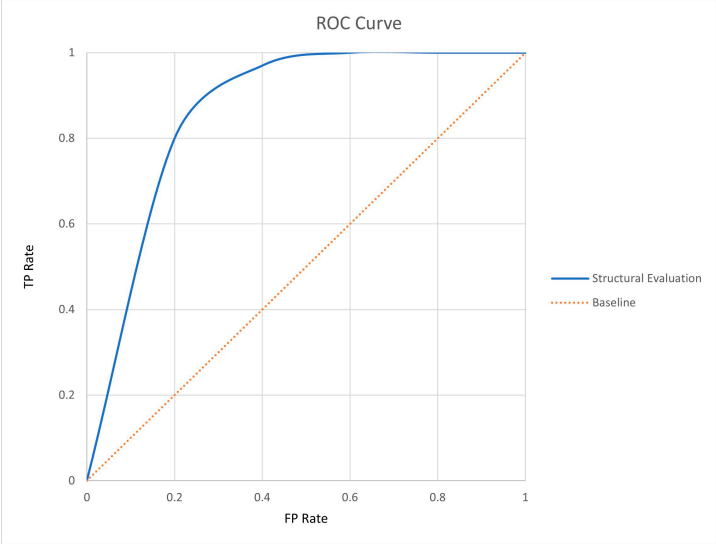


Figure 4. Sample ROC curve.

For the AdaBoost-MLP algorithm used in this study, a bridge model for predicting four conditional levels was established, and a total of four models were developed in this process. For model accuracy, the accuracy results of the four models were similar, ranging from 77.62% to 89.02%. The precision was between 0.8 and 0.86, the recall was between 0.82 and 0.91, and the F-score was between 0.82 and 0.88. The AUC under ROC curve size was 0.853–0.953.

Possible reasons for the differences in the evaluation indicators of the above model are as follows:

(1) The quantity and quality of the data determine the accuracy of the computation outputs for ML models. Data requirements for different ML models vary, but in general, the more data there are and the greater their quality, the more accurate the trained model will be. The more characteristics, regularities, and subtleties the model can learn, the higher the prediction capability of the model will be due to the abundance and high quality of the data.

(2) Existing studies [7,22] have demonstrated that the inconsistent data distribution in the output variables is what causes the high accuracy and low recall of model computation outcomes. The four prediction models employed in this investigation were feature engineered, and there was no clear imbalance in the distribution of the data used. As a result, recall and other metrics did not significantly affect how accurate the four models' calculations were.

4.2. Predictor Importance Results

The predictor importance results helped to reassess the significance of each input variable to the output variables that directly reflects the bridge conditions. The results are shown in Table 7, where zero denotes the least importance and one the greatest importance.

Table 7. Predictor importance results.

Input Variables	Superstructure Condition	Substructure Condition	Structural Evaluation	Deck Condition	Average
Design load	0.09	0.08	0.07	0.09	0.08
Age	0.11	0.08	0.08	0.04	0.08
Kind of material and/or design	0.09	0.08	0.06	0.04	0.07
Functional classification of inventory route	0.07	0.08	0.06	0.09	0.07
Type of design and/or construction	0.09	0.08	0.06	0.03	0.07
Deck structure type	0.09	0.08	0.06	0.03	0.07
Length of maximum span	0.09	0.08	0.06	0.03	0.07
Type of wearing surface	0.09	0.08	0.06	0.02	0.06
Maintenance responsibility	0.04	0.04	0.06	0.09	0.06
Inventory route, total horizontal clearance	0.04	0.06	0.03	0.09	0.06
Deck width, out-to-out	0.04	0.06	0.03	0.09	0.06
Inventory route	0.03	0.04	0.06	0.09	0.06
Type of service under bridge	0.02	0.05	0.06	0.07	0.05
Lanes on and under the Structure	0.05	0.04	0.02	0.03	0.04
Deck protection	0.02	0.03	0.06	0	0.03
ADTT	0	0	0.02	0.09	0.03
ADT	0.01	0.01	0.02	0.05	0.02
Minimum vertical under clearance	0.02	0.02	0.04	0.01	0.02
Structural length	0.01	0	0.04	0.02	0.01
Type of membrane	0	0.01	0.05	0	0.01

As seen in Table 7, the two most significant influencing factors of bridge state are age and design load, and other characteristics like bridge deck wear surface type, material, or design type (e.g., bridge span, length, ADT, etc.) are also important influencing factors of the bridge state. This is in line with previous research findings [10], and the findings of this study support the significance of structural aspects in the collapse of multimaterial bridges and complicated structural designs.

In this section, the bridge condition prediction model analysis yields a more general effect of bridge age and design loads. In terms of bridge age, the majority of bridges below 45 years old are structurally assessed as good, and a larger proportion of bridges with a bridge age above 45 years old are in poor condition. Therefore, the cost of inspecting bridges that have been serving for more than 45 years should be enhanced in the management program. In addition, the visualization of bridge factors helps to interpret and analyze physical and environmental factors impacting bridge conditions. Comprehensive consideration of these factors in inspection and scheduling guides is recommended for accurate control and cost savings.

This study also compared its results with existing studies from recent years as shown in Table 8.

Table 8. Comparison with existing study.

	Author	Number of Bridges	Accuracy	Precision	Recall	F-Score	AUC
Existing Study	Hussaini	95	84.21%	0.84	0.84	0.83	0.79
	Allah	Unknown	79.67%			0.81	
	Alogdianakis	223,369	72.6%	0.78	0.76	0.77	
	Creary	5000	89.95%				
Proposed Study		55,476	89.02%	0.84	0.82	0.83	0.95

As can be seen, the proposed study outperforms the majority of current studies in terms of data volume, model accuracy, and other evaluation metrics.

5. Case Study

This section presents a case study to show how the developed prediction model can be used to support the bridge management process because there is still very little information on elucidating the connection between theoretical models and practical applications.

The comparison flowchart between the approach for bridge inspection currently in use and the suggested model is shown in Figure 5. According to the current bridge management plan, an inspector will conduct the inspection work if the bridge is due for inspection the following year. The data will be incorporated into this study's bridge structural prediction model as part of the suggested management scheme, and the bridges with a poor prediction status will be scheduled for inspection based on the prediction results if the bridge has to be examined the following year.

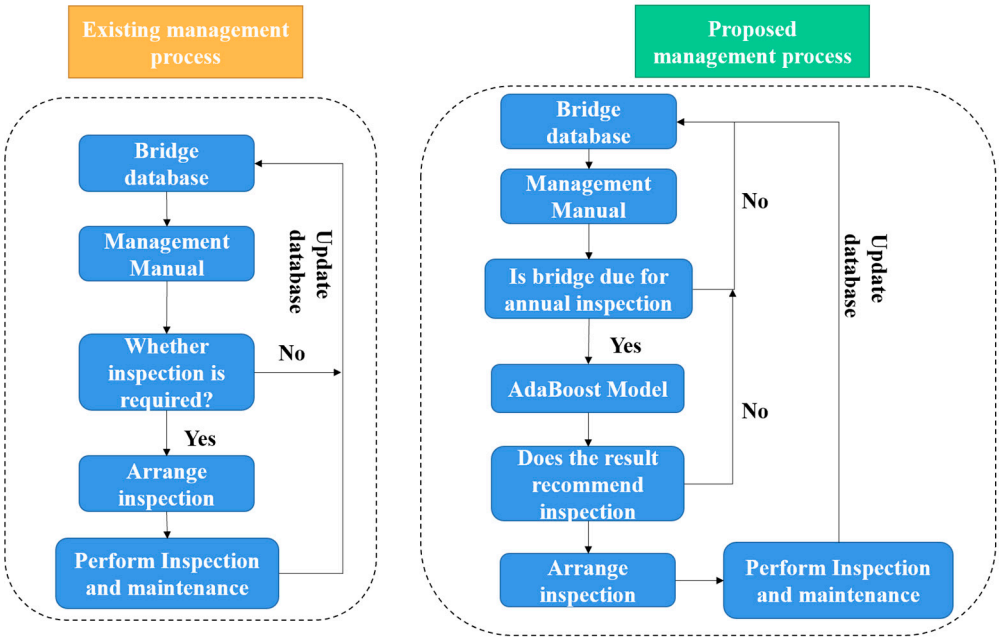


Figure 5. Flowchart of the proposed model implementation.

Data from the NBI for 9427 bridges in South Carolina were used in this case study. It is important to note that this case study's predictive model was developed using structural evaluation as an output variable. Data pre-processing was finished with feature engineering processing to create valid data for the machine-learning model, leaving a total of 9421 bridges for the subsequent analysis. Finding the bridges that needed to be looked at in the upcoming year was the next step. It was ultimately decided that 4494 bridges will be evaluated in the upcoming year based on the bridge data that was published by FHWA and an examination of the bridge inspection manual. The AdaBoost model was fed data on the bridges that would be subjected to inspection the following year. If the model indicated that the bridges were in need of structural repair, the bridges were scheduled for inspection the following year; otherwise, they were not. The prediction results are shown in Figure 6 and Table 9.

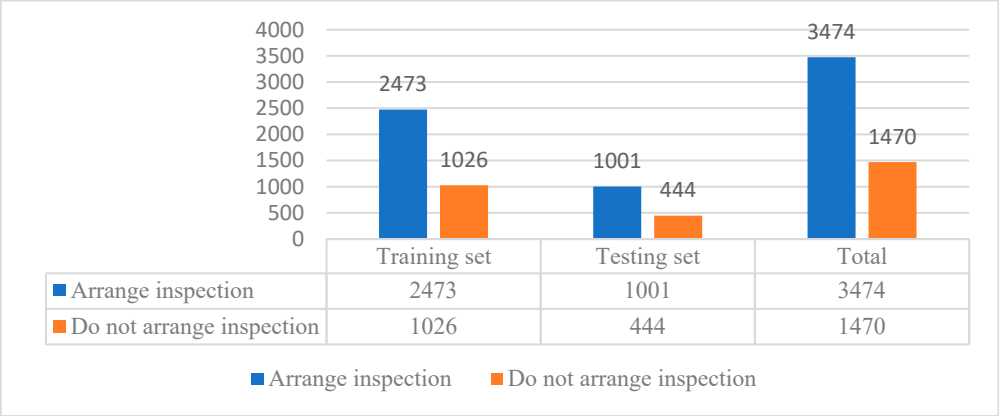


Figure 6. Forecast results of bridge inspection in South Carolina.

Table 9. South Carolina model prediction results.

	Accuracy	Precision	Recall	F-Score	AUC
Training set	94.23%	0.89	0.90	0.89	0.95
Testing set	94.33%	0.90	0.91	0.90	0.95

The number of bridges scheduled for inspection in 2019 was decreased from 4494 to 3474, as predicted in Figure 6. The improved prediction model can reach an accuracy of 94.23%, as shown in Table 9. In terms of data volume and prediction accuracy, the machine-learning model utilized in this instance is more stable and capable of a higher performance than those in most other studies. This case study explains how the established AdaBoost model was put into practice, and it can serve as a valuable resource for those who work in the field of bridge maintenance and related fields to forecast the structural status of bridges. The bridge management procedure is now more selective as a result of the model prediction results, which indicate that around 29.73% of the scheduled bridge inspections are saved.

6. Conclusions and Future Works

This study aims to enhance bridge maintenance and inspection using predictive machine-learning algorithms. It presents a complete model development process, from feature engineering to evaluation, and demonstrates its practical value in civil infrastructure management. The study highlights the importance of boosted ML models and predictor importance analysis in bridge management, focusing on key factors.

The main conclusions drawn from this study are presented below:

(1) During the creation and evaluation of the prediction models, it was found that the AdaBoost model reported in this study had more consistent overall results in terms of accuracy, precision, recall, F-score, and ROC curve. It is reasonable to conclude that the suggested strategy of creating boosted ML models has improved the current application of ML in bridge management operations based solely on the comparison results with prior studies.

(2) Based on the current bridge management system, it is advised to include other variables in the inspection scheduling criteria in order to achieve accurate control and cost savings. The prediction importance results show that bridge age and design load are the two most significant variables affecting the state of the bridge.

(3) The case study demonstrates the model's practical applicability. It can significantly reduce the resources needed for bridge maintenance and has a high potential for practical application and translation.

Future Works

It should be noted that the binary classification process used in the proposed model prevents it from being able to distinguish between bridges in critical condition, due to their small sample sizes; thus, if bridges in critical condition are chosen as the research target, additional data collection and model development studies should be conducted.

In addition, future topics can be studied including but not limited to the following:

(1) Real-Time Structural Health Monitoring: Develop smarter sensor technologies and monitoring systems that can monitor the health of bridge structures in real time, identify potential problems, and provide predictive maintenance recommendations.
(2) Extreme Weather Predictions: Introducing more environmental factors into consideration, including studies of the climate resilience of bridges to withstand the impacts of climate change and extreme weather events on infrastructure.
(3) Sustainable Development: Research into new bridge building materials, including more environmentally friendly and cost–benefit-analyzed materials, to improve the longevity and resilience of bridges.

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References

1. South Carolina Department of Transportation. *US Department of Transportation Federal Highway Administration*; South Carolina Department of Transportation: Columbia, SC, USA, 2001.
2. Flah, M.; Nunez, I.; Ben Chaabene, W.; Nehdi, M.L. Machine learning algorithms in civil structural health monitoring: A systematic review. *Arch. Comput. Methods Eng.* **2021**, *28*, 2621–2643. [CrossRef]
3. US Nuclear Regulatory Commission; US Nuclear Regulatory Commission; Division of Rules, Records; US Nuclear Regulatory Commission; Division of Freedom of Information; Publications Services; US Nuclear Regulatory Commission; Division of Administrative Services. *Rules and Regulations*; Nuclear Regulatory Commission, Office of Administration, Division of Rules and Records: Rockville, MD, USA, 1987; Volume 2.
4. Alghawazi, M.; Alghazzawi, D.; Alarifi, S. Deep Learning Architecture for Detecting SQL Injection Attacks Based on RNN Autoencoder Model. *Mathematics* **2023**, *11*, 3286. [CrossRef]
5. Nguyen, H.V.; Byeon, H. Predicting Depression during the COVID-19 Pandemic Using Interpretable TabNet: A Case Study in South Korea. *Mathematics* **2023**, *11*, 3145. [CrossRef]
6. Zhang, Z.; Xiao, Y.; Fu, Z.; Zhong, K.; Niu, H. A study on early warnings of financial crisis of Chinese listed companies based on DEA–SVM model. *Mathematics* **2022**, *10*, 2142. [CrossRef]
7. Gao, C.; Elzarka, H. The use of decision tree based predictive models for improving the culvert inspection process. *Adv. Eng. Inform.* **2021**, *47*, 101203. [CrossRef]
8. Aragonés Lozano, M.; Pérez Llopis, I.; Esteve Domingo, M. Threat Hunting System for Protecting Critical Infrastructures Using a Machine Learning Approach. *Mathematics* **2023**, *11*, 3448. [CrossRef]
9. Yang, J.; Xiang, F.; Li, R.; Zhang, L.; Yang, X.; Jiang, S.; Zhang, H.; Wang, D.; Liu, X. Intelligent bridge management via big data knowledge engineering. *Autom. Constr.* **2022**, *135*, 104118. [CrossRef]
10. Lim, S.; Chi, S. Xgboost application on bridge management systems for proactive damage estimation. *Adv. Eng. Inform.* **2019**, *41*, 100922. [CrossRef]

11. Czepiel, E. *Bridge Management Systems Literature Review and Search*; Infrastructure Technology Institute (ITI): Evanston, IL, USA, 1995.
12. Li, X.; Li, Y.; Guo, Y.; Qin, H. Information fusion between bridge management system and structure health monitoring system. *Highlights Sci. Eng. Technol.* **2022**, *28*, 310–315. [CrossRef]
13. Lauridsen, J.; Lassen, B. The Danish bridge management system DANBRO. In *Management of Highway Structures*; Thomas Telford Publishing: London, UK, 1999; pp. 61–70.
14. Gholami, M.; Sam, A.R.B.M.; Yatim, J.M. Assessment of bridge management system in Iran. *Procedia Eng.* **2013**, *54*, 573–583. [CrossRef]
15. Liu, H.; Zhang, Y. Bridge condition rating data modeling using deep learning algorithm. *Struct. Infrastruct. Eng.* **2020**, *16*, 1447–1460. [CrossRef]
16. Wang, R.; Ma, L.; Yan, C.; Mathew, J. Condition deterioration prediction of bridge elements using Dynamic Bayesian Networks (DBNs). In Proceedings of the 2012 International Conference on Quality, Reliability, Risk, Maintenance, and Safety Engineering, Chengdu, China, 15–18 June 2012; pp. 566–571.
17. Alogdianakis, F.; Dimitriou, L.; Charmpis, D.C. Data-driven recognition and modelling of deterioration patterns in the US National Bridge Inventory: A genetic algorithm-artificial neural network framework. *Adv. Eng. Softw.* **2022**, *171*, 103148. [CrossRef]
18. Woodward, R.; Cullington, D.; Daly, A.; Vassie, P.; Haardt, P.; Kashner, R.; Astudillo, R.; Velando, C.; Godart, B.; Cremona, C. *Bridge Management in Europe (BRIME)-Deliverable D14-Final Report*; Transport Research Laboratory: Wokingham, UK, 2001.
19. Wan, C.; Zhou, Z.; Li, S.; Ding, Y.; Xu, Z.; Yang, Z.; Xia, Y.; Yin, F. Development of a bridge management system based on the building information modeling technology. *Sustainability* **2019**, *11*, 4583. [CrossRef]
20. Johnson, J.; Boyle, Z. Implementation of AASHTOWare Bridge Management 5.2. 3 to meet agency policies and objectives for bridge management and address FHWA requirements. In Proceedings of the Eleventh International Bridge and Structures Management Conference, Mesa, AZ, USA, 25–27 April 2017; p. 188.
21. Dong, C.-Z.; Catbas, F.N. A review of computer vision–based structural health monitoring at local and global levels. *Struct. Health Monit.* **2021**, *20*, 692–743. [CrossRef]
22. Gao, C. Use of Data Analytics and Machine Learning to Improve Culverts Asset Management Systems. Ph.D. Thesis, University of Cincinnati, Cincinnati, OH, USA, 2019.
23. Sun, L.; Shang, Z.; Xia, Y.; Bhowmick, S.; Nagarajaiah, S. Review of bridge structural health monitoring aided by big data and artificial intelligence: From condition assessment to damage detection. *J. Struct. Eng.* **2020**, *146*, 04020073. [CrossRef]
24. Ilbeigi, M.; Ebrahimi Meimand, M. Statistical forecasting of bridge deterioration conditions. *J. Perform. Constr. Facil.* **2020**, *34*, 04019104. [CrossRef]
25. Wu, C.; Wu, P.; Wang, J.; Jiang, R.; Chen, M.; Wang, X. Critical review of data-driven decision-making in bridge operation and maintenance. *Struct. Infrastruct. Eng.* **2021**, *18*, 47–70. [CrossRef]
26. Wellalage, N.K.W.; Zhang, T.; Dwight, R. Calibrating Markov chain–based deterioration models for predicting future conditions of railway bridge elements. *J. Bridge Eng.* **2015**, *20*, 04014060. [CrossRef]
27. Agrawal, A.K.; Kawaguchi, A.; Chen, Z. Deterioration rates of typical bridge elements in New York. *J. Bridge Eng.* **2010**, *15*, 419–429. [CrossRef]
28. Lee, J.; Sanmugarasa, K.; Blumenstein, M.; Loo, Y.-C. Improving the reliability of a Bridge Management System (BMS) using an ANN-based Backward Prediction Model (BPM). *Autom. Constr.* **2008**, *17*, 758–772. [CrossRef]
29. Ghiasi, A.; Ng, C.-T.; Sheikh, A.H. Damage detection of in-service steel railway bridges using a fine k-nearest neighbor machine learning classifier. In *Structures*; Elsevier: Amsterdam, The Netherlands, 2022; pp. 1920–1935.
30. Callow, D.; Lee, J.; Blumenstein, M.; Guan, H.; Loo, Y.-C. Development of hybrid optimisation method for Artificial Intelligence based bridge deterioration model—Feasibility study. *Autom. Constr.* **2013**, *31*, 83–91. [CrossRef]
31. Fabianowski, D.; Jakiel, P.; Stemplewski, S. Development of artificial neural network for condition assessment of bridges based on hybrid decision making method–Feasibility study. *Expert Syst. Appl.* **2021**, *168*, 114271. [CrossRef]
32. Fang, Z.; Roy, K.; Ma, Q.; Uzzaman, A.; Lim, J.B. Application of deep learning method in web crippling strength prediction of cold-formed stainless steel channel sections under end-two-flange loading. In *Structures*; Elsevier: Amsterdam, The Netherlands, 2021; pp. 2903–2942.
33. Philip, R.E.; Andrushia, A.D.; Nammalvar, A.; Gurupatham, B.G.A.; Roy, K. A Comparative Study on Crack Detection in Concrete Walls Using Transfer Learning Techniques. *J. Compos. Sci.* **2023**, *7*, 169. [CrossRef]
34. Cardellicchio, A.; Ruggieri, S.; Nettis, A.; Renò, V.; Uva, G. Physical interpretation of machine learning-based recognition of defects for the risk management of existing bridge heritage. *Eng. Fail. Anal.* **2023**, *149*, 107237. [CrossRef]
35. Jaafaru, H.; Agbelie, B. Bridge maintenance planning framework using machine learning, multi-criteria decision analysis and evolutionary optimization models. *Autom. Constr.* **2022**, *143*, 104585. [CrossRef]
36. Gordan, M.; Sabbagh-Yazdi, S.-R.; Ismail, Z.; Ghaedi, K.; Carroll, P.; McCrum, D.; Samali, B. State-of-the-art review on advancements of data mining in structural health monitoring. *Measurement* **2022**, *193*, 110939. [CrossRef]
37. Jiang, Y.; Yang, G.; Li, H.; Zhang, T. Knowledge driven approach for smart bridge maintenance using big data mining. *Autom. Constr.* **2023**, *146*, 104673. [CrossRef]

38. Creary, P.A.; Fang, F.C. The data mining approach for analyzing infrastructure operating conditions. *Procedia-Soc. Behav. Sci.* **2013**, *96*, 2835–2845. [CrossRef]
39. Shan, Y.; Contreras-Nieto, C.; Lewis, P. Using data analytics to characterize steel bridge deterioration. *Constr. Res. Congr.* **2016**, *2016*, 1691–1699.
40. Huang, Q.; Ong, K.-L.; Alahakoon, D. Improving Bridge Deterioration Modelling Using Rainfall Data from the Bureau of Meteorology. In Proceedings of the 13th Australasian Data Mining Conference (AusDM 2015), Sydney, Australia, 8–9 August 2015; pp. 161–167.
41. Fatourechi, M.; Ward, R.K.; Mason, S.G.; Huggins, J.; Schlögl, A.; Birch, G.E. Comparison of evaluation metrics in classification applications with imbalanced datasets. In Proceedings of the 2008 Seventh International Conference on Machine Learning and Applications, San Diego, CA, USA, 11–13 December 2008; pp. 777–782.
42. Hossin, M.; Sulaiman, M.N. A review on evaluation metrics for data classification evaluations. *Int. J. Data Min. Knowl. Manag. Process* **2015**, *5*, 1.
43. Salem, O.; Salman, B.; Najafi, M. Culvert asset management practices and deterioration modeling. *Transp. Res. Rec.* **2012**, *2285*, 1–7. [CrossRef]
44. Tatari, O.; Sargand, S.M.; Masada, T.; Tarawneh, B. Neural network approach to condition assessment of highway culverts: Case study in Ohio. *J. Infrastruct. Syst.* **2013**, *19*, 409–414. [CrossRef]
45. Tran, H.D. Investigation of deterioration models for stormwater pipe systems. Ph.D. Thesis, Victoria University, Melbourne, Australia, 2007.
46. Spruce, M.D.; Arthur, R.; Robbins, J.; Williams, H.T. Social sensing of high-impact rainfall events worldwide: A benchmark comparison against manually curated impact observations. *Nat. Hazards Earth Syst. Sci.* **2021**, *21*, 2407–2425. [CrossRef]
47. Miao, J.; Zhu, W. Precision–recall curve (PRC) classification trees. *Evol. Intell.* **2022**, *15*, 1545–1569. [CrossRef]
48. Fawcett, T. An introduction to ROC analysis. *Pattern Recognit. Lett.* **2006**, *27*, 861–874. [CrossRef]
49. Japkowicz, N.; Shah, M. *Evaluating Learning Algorithms: A Classification Perspective*; Cambridge University Press: Cambridge, UK, 2011.
50. Bukhsh, Z.A.; Stipanovic, I.; Saeed, A.; Doree, A.G. Maintenance intervention predictions using entity-embedding neural networks. *Autom. Constr.* **2020**, *116*, 103202. [CrossRef]
51. Ali, G.; Elsayegh, A.; Assaad, R.; El-adaway, I.H.; Abotaleb, I.S. Artificial neural network model for bridge deterioration and assessment. In Proceedings of the 2019 Canadian Society for Civil Engineering Annual Conference, CSCE 2019, Montreal, QC, Canada, 12–15 June 2019.
52. Lan, Y.; Zhang, Y.; Lin, W. Diagnosis algorithms for indirect bridge health monitoring via an optimized AdaBoost-linear SVM. *Eng. Struct.* **2023**, *275*, 115239. [CrossRef]
53. Samadi, D.; Taghaddos, H.; Nili, M.H.; Noghabaei, M. Development of a bridge maintenance system using bridge information modeling. *Civ. Eng. Infrastruct. J.* **2021**, *54*, 351–364.
54. Stehlik-Barry, K.; Babinec, A.J. *Data Analysis with IBM SPSS Statistics*; Packt Publishing Ltd.: Birmingham, UK, 2017.

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