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Bridge Deck Deterioration: Reasons and Patterns

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Abstract

The deck condition of bridges is one of the most important factors impacting the connectivity and efficiency of transportation networks. Bridges with quickly deteriorating deck conditions are a huge financial burden for transportation agencies and can downgrade the efficiency of the whole transportation network. This study utilizes an interpretable machine learning framework, Shapley additive explanation (SHAP), to investigate the associations between various factors, such as wearing surface, deck structure, and so forth, and bridges with quickly deteriorating deck conditions nationwide. An XGBoost model is trained to perform the binary classification task on a heavily imbalanced dataset and classify relatively young bridges (less than 20 years old) with poor/fair deck conditions and relatively old bridges (30–40 years old) with good deck conditions in the National Bridge Inventory (NBI) database. The accuracy of the predictive model is 0.91, and the AUC score is about 0.83. After applying this well-performed predictive model on the interpretable machine learning framework, the results revealed that without wearing surface, corrugated steel deck structure, wide bridge structure, and long span are highly associated with bridges with quickly deteriorating decks. The results also show that bridges with a relatively low average daily traffic (ADT) or truck percentage of ADT are in a dilemma zone, where the overall traffic or truck volume of the bridge is not low enough to prevent fast deterioration, but not high enough for eligibility for the funding required for more durable materials during construction or appropriate maintenance.

Keywords

data and data science, artificial intelligence and advanced computing applications, artificial intelligence, data analytics, machine learning (artificial intelligence), pattern recognition, infrastructure, construction, bridges and structures, infrastructure management and system preservation, bridge and structures management, bridge condition data/assessment, bridge data QC/QA

The bridge is a critical component of transportation infrastructure, providing a safe means to span a physical obstacle without influencing what lies underneath. Bridges increase transportation efficiency and reliability, lower costs, and promote employment and economic development (*1*). There are more than 618,000 bridges in the United States transportation system, over 590,000 of which are in the highway network, comprising more than 6,000 total miles in length (*2*). Some 23% of all bridges are located on urban highways, including urban interstate and arterial highways, and these bridges have most of the average daily traffic (ADT)—about 73% of all bridge-crossing traffic in the United States (*3*). The deck is the surface of a bridge, and it directly transmits vehicle loads to other supporting structures. The durability of bridge decks degrades more quickly than that of other parts of the bridge because of damage and deterioration caused by direct exposure to physicochemical factors (*4*). In some specific areas, the substructures and superstructure of bridges are in relatively good structural condition, but the bridge decks deteriorate or age more rapidly as a result of high traffic volumes, the use of deicing agents, and weather effects, long span (*5*, *6*). In the worst cases, if bridge deck improvement is needed, there are extra construction costs, and traffic jams and delays may occur (*7*). Therefore, deck condition is essential for bridge functioning, and routine inspection is critical. A

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thorough understanding of the factors resulting in quickly deteriorating bridge decks and building a deck condition prediction model could effectively assist transportation agencies in planning the maintenance, repair, and rehabilitation of bridges, which could prolong the service life of bridges.

There is abundant literature on deck condition prediction and corresponding factor analysis, from the regression model (*8–14*) and Markov Chain (*15–20*) to Monte Carlo simulation (*16*, *19*, *21*). Lee et al. developed a linear regression model to analyze the correlation between the deterioration of highway bridge decks and weather-related variables, including the number of snowy days, the amount of snowfall, the number of freeze–thaw days, and the average winter temperature (*12*). In another study, Ghonima et al. applied a random parameters binary logistic regression to analyze environmental and structural parameters (*9*); they found that the following variables are significant: average daily truck traffic, climate region, distance from seawater, bridge deck area, age of the bridge, type of design and/or construction, structural material design, deck protection, type of membrane, wearing surface, and maintenance responsibility. Hasan and Elwakil used stochastic regression analysis to model the impact of explanatory variables, including ADT, structure length, deck width, roadway width, skew degrees, max span length, and inspection frequency on deck condition (*10*). Morcous et al. combined genetic algorithms and the Markovian deterioration model for concrete bridge decks to analyze the environmental variables, such as highway class, region, ADT, and percentage of truck traffic (*22*). Morcous developed transition probability matrices for different elements of deck condition and utilized deck inspection data and Bayes' rule to adjust the Markov Chains (*20*). The results illustrated that the deck condition independence assumption from Markov Chains is acceptable with a 95% level of confidence. However, the Markov Chain prediction could be biased, depending on the parameters of transition probabilities. To decrease the bias, the Monte Carlo simulation methods were presented. The experiment indicated that the simulation prediction model has better prediction accuracy (*16*).

On the other hand, data-driven approaches are becoming increasingly popular in prediction in recent years (*23*). Compared with conventional statistical models, data-driven approaches have demonstrated their accuracy, especially with high-dimensional large datasets or sparse datasets (*24*). Therefore there are more and more studies utilizing sufficient and appropriate data to predict or evaluate the deck condition, such as actual bridge deck survey data (*24–26*), ground-penetrating radar data (*27*, *28*), and National Bridge Inventory (NBI) data (*29*, *30*). Nguyen and Dinhapplied the Artificial Neural Network (ANN) to predict future deck conditions in Alabama, United States (*31*). The model accuracy was between 73.6% and 98.5%, with a margin error of ± 1. Moreover, Inkoom et al. employed ADT, truck factor, roadway functional class, asphalt thickness, and pavement condition time series data in recursive partitioning and used an ANN model to predict the rating of pavement (*32*). In comparison, Huang used ANN classification on Wisconsin's concrete bridges to predict deck condition ratings based on geometrical, functional, and environmental factors (*25*). Similarly, decision-tree classification algorithms have been used to model deck deterioration (*24*). Assaad and EI-adaway developed an ANN and *k*-nearest neighbors (KNNs)-based bridge management system to assess and predict bridge deck deterioration conditions (*29*). Liu and Zhang utilized convolutional neural network models and bridge data from the Federal Highway Adminstration (FHWA) for three primary components of Maryland highway bridges: deck, superstructure, and substructure, which have been trained and validated (*33*). Rafiq et al. considered the complex interdependencies within elements of engineering systems, and then applied the Bayesian Belief Network to build a condition-based deterioration model at the bridge-group level (*34*).

In the past, many studies utilized various models to predict deck conditions and explore the impact of certain factors affecting deck deterioration. However, the majority of these studies only consider a certain type of bridge deck, like concrete (*19*, *30*, *35*), or a limited number of bridges only in certain geographical areas (*9*, *24*, *29*, *33*, *36*). Only a few studies have used nationwide bridge data for such studies. Moreover, for all bridges built after 1980 in the NBI, there are 1,635 bridges built in the past 20 years with deck conditions that are poor or fair, whereas 32,148 bridges built at least 30 years ago have decks in good condition. These bridges with quickly deteriorating decks could be a huge burden on transportation agencies financially. Meanwhile, they could lead to inefficiency of the whole transportation network. An in-depth understanding of these bridges with quickly deteriorating decks is important and necessary. To the knowledge of the authors, there are no published articles that compare bridges with quickly deteriorating decks to relatively older bridges with decks in good condition. This paper used a nationwide bridge database to understand why the deck condition of some relatively young bridges deteriorates faster than others and why the deck condition of some fairly old bridges is still good without reconstruction.

Many machine learning algorithms, such as random forest, gradient boosting, and neural network have been applied in predicting deck conditions. The machine learning algorithms generally perform better than conventional statistical modeling, but the interpretability of the result is the main weakness. For conventional statistical models and many machine learning algorithms, imbalanced data is a problem that cannot be easily handled. Therefore, this study adopts the XGBoost algorithm for building the predictive model. The XGBoost is outstanding in classification tasks, such as predicting deck conditions, for its high prediction accuracy, the ability to handle imbalanced data, and its computational efficiency (*37–39*). To tackle the interpretability issue, this study utilized an interpretable machine learning framework—Shapley additive explanation (SHAP) (*40*). SHAP is a framework based on game theory to reveal the marginal effects of features through local interpretability (*40*). More mathematical details about SHAP will be discussed in the methodology section.

Thus, this study first builds the predictive model using XGBoost and then utilizes an interpretable machine learning framework—SHAP—to explore the associations of these quickly deteriorating decks and various factors. The research question is formulated as a binary classification task: relatively young bridges (less than 20 years old) with poor/fair deck conditions versus relatively old bridges (between 30 years old and 40 years old) with good deck conditions. After the predictive model is trained, it is applied to the SHAP framework. Therefore, the associations between these quickly deteriorating decks and various factors can be revealed.

Methods

Problem Formulation

The research problem is formulated as a binary classification task. Two categories are created to measure the fast deterioration deck condition. One category is the young_poor, and another is old_good. For young_poor, it stands for bridges under 20 years old (from 2000–2020) with poor/fair deck conditions. For old_good, it means bridges between 30–40 years old (from 1980–1990) with good deck condition. The young_poor bridges are the ones with quickly deteriorating decks. To fit the classification model, the young_poor cases are considered positive cases and equals 1, and the old_good cases are treated as negative cases and equals 0.

Figure 1 shows the flow chart of data processing and the modeling process. The detailed parameters tuning for the XGBoost model will be discussed in the XGBoost model section below.

XGBoost

XGBoost is a general tree boosting algorithm. First, a tree is trained by using the features and targets of the training set, then the predicted values of each sample are obtained, and the residual between the predicted value and true value is calculated. Next, when training other trees, the residual is taken as the goal, and the algorithm will stop when the total tree number reaches the setting or when the error of the verification set reaches the threshold. Finally, each tree's output sample value is added, which is the final predicted value of the sample.

XGBoost's objective function in Equation 1 has two parts. The first part is used to measure the difference between the predictive values and true value, and the second part is the regularization term. The regularization term also contained two parts, shown in Equation 2. T represents the number of leaf nodes, and w represents the score of leaf nodes. γ can control the number of leaf nodes, λ can control the score of leaf nodes will not be too large, to prevent overfitting.

$$Obj = \sum_{i=1}^{n} l(y_i, \hat{y}_i) + \sum_{k=1}^{K} \Omega(f_k) \tag{1}$$

$$\Omega(f) = \gamma T + \frac{1}{2}\lambda \|w\|^2 \tag{2}$$

The newly generated tree is to fit the residual of the last prediction. After the t tree is generated, the predictive value can be written as Equation 3. Then, the objective function could be changed to Equation 4. XGBoost implements Taylor approximation to find f_t to minimize the objective function.

$$y_i^{(t)} = \hat{y}_i^{(t-1)} + f_t(x_i) \tag{3}$$

$$Obj^{(t)} = \sum_{i=1}^{n} l\left(y_i, \hat{y}_i^{(t-1)} + f_t(x_i)\right) + \Omega(f_t) \tag{4}$$

$$Obj^{(t)} \cong \sum_{i=1}^{n} \left[l\left(y_i, \hat{y}_i^{(t-1)}\right) + g_i f_t(x_i) + \frac{1}{2} h_i f_t^2(x_i) \right] + \Omega(f_t) \tag{5}$$

where

g_i is the first-order gradient statistic on the loss function;

h_i is the second-order gradient statistic on the loss function.

The primary aim of the XGBoost is to develop a classification model between young bridges with poor condition and old bridges with good condition, not only predicting the deck performance but also analyzing the importance of contributing factors. The hyperparameters' tuning is critical for the precision and overfitting prevention of the model. According to Occam's razor principle, the model should not be complicated unnecessarily, so that the following hyperparameters are selected to optimize the model with grid search and 10-fold cross-validation. The learning_rate is a parameter that improves the stability of the model and reduces

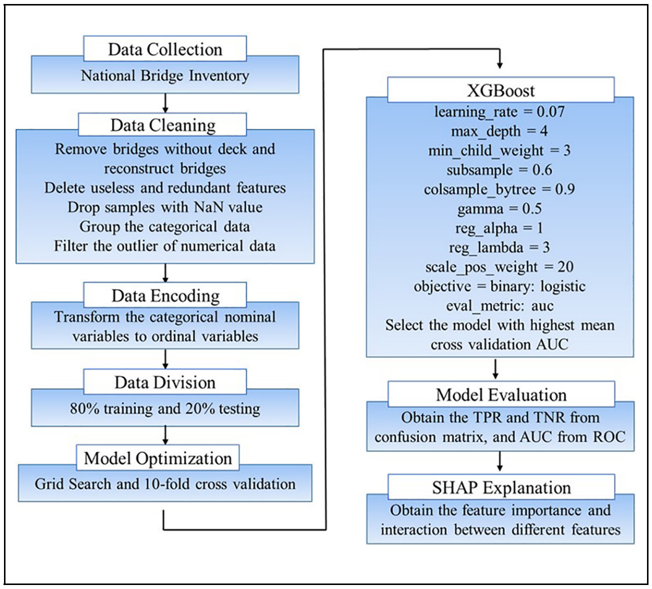

Figure 1. The flow chart of data prepocessing and proposed model.
Note: AUC = area under the ROC curve; ROC = receiver operating characteristic; SHAP = Shapley additive explanation; TNR = true negative rate; TPR = true posistive rate; NaN = the value is undefined or unpresentable.

overfitting. The smaller the parameter is, the more learning space for the further trees. Max_depth controls the maximum number of nodes in the tree model. Increasing the number will increase the complexity of the model and reduce the generalization ability of the model. Min_child_weight is to stop the node splitting, which effectively prevents the overfitting and learning from special samples. Subsample manages the proportion of random sampling of each tree. If the number is small, the algorithm will be more conservative. However, the model may be underfitting if the number is too small. Colsample_bytree is used to control the percentage of features randomly sampled per tree. In the case of node splitting, the node will be split only if the decreased value of the loss function is greater than the minimum loss reduction required for node splitting. Reg_alpha could help faster algorithm coverage in the case of the high-dimensional dataset. Reg_lambda is to control the regularization part of XGBoost and to reduce the overfitting. When the dataset is imbalanced, setting scale_pos_weigh to the ratio of the number of negative samples to the number of positive samples would improve the model to better distinguish between positive and negative samples. Last but not least, the number of estimators is determined by cross-validation so that the parameter has no need for manual setting.

SHAP

The SHAP is a method to interpret the result of the machine learning technique. Lundberg and Lee proposed SHAP to explain the tree-based machine learning model by estimating the contribution of each feature prediction based on the game-theoretic approach (*40*). The feature's importance is determined by calculating the contribution of the single feature in the total features. The steps are to calculate the income of a feature in the combination and subtract the benefit when the combination does not include this feature, then calculate all combinations and weighted average to get the overall contribution of the feature. The Shapley value estimation is calculated by Equation 6. The Shapley value evaluates the sum of marginal contribution of feature *i* across each subset of the whole feature.

$$\Phi_j(val) = \sum_{S\subseteq\{x_1\ldots x_p\}\setminus\{x_j\}} \frac{|S|!(p-|S|-1)!}{p!}(val(S\cup\{x_j\}) - val(S)) \quad (6)$$

where
P is the set contains all feature;
xj is the feature i;
S is one of the subsets of P; and,
$val(\cdot)$ refers to the trained model with the feature.

Model Evaluation

The confusion matrix, a two-dimensional matrix with abscissa as the prediction result and ordinate as the true value, is an effective and useful evaluation tool in classification. Many metrics can be calculated through the confusion matrix, such as accuracy, precision, recall, and F1 score. However, the young bridge with poor deck condition is imbalanced by nature, and the minority group is more likely to be misclassified. Therefore, this study considers the two measurements from the confusion matrix to evaluate the model's performance to the majority and minority group: True Positive Rate (TPR) and True Negative Rate (TNR), as shown in Equations 7 and 8. In the proposed model, the TPR is calculated as the number of the correct old bridge with good deck condition occurrence prediction divided by the total number of the old bridge with good deck condition in the testing dataset. The TNR represents the ratio of correct prediction of the young bridge with poor deck condition to the total number of the young bridge with poor deck condition in the testing dataset. These two metrics range from 0 to 1, where 0 indicates the imprecise and 1 indicates the accuracy. Besides, the Receiver Operating Characteristic curve is another classification metric based on False Positive Rate and TPR. The area under the ROC curve, which also is called AUC, is selected to evaluate the model's ability to classify positive and negative conditions under an imbalanced dataset. The AUC ranges from 0.5

to 1, where 0.5 indicates the worst and 1 indicates the best. Other commonly used performance measurements, like precision and F1 score, also can be derived from TPR and TNR.

$$\mathrm{TPR} = \frac{\mathrm{Num(true\ positive\ assessments)}}{\mathrm{Num(all\ positive\ assessments)}} \quad (7)$$

$$\mathrm{TNR} = \frac{\mathrm{Num(true\ negative\ assessments)}}{\mathrm{Num(all\ negative\ assessments)}} \quad (8)$$

Data Preparation

This study uses the NBI, which is maintained by FHWA and includes all highway bridges more than 20 ft long used for vehicular traffic in the United States. The database contains detailed information about location, structure type and materials, inspection, condition evaluation, traffic data, and climate data. Therefore, the NBI data are a valuable and solid resource for exploring bridge deterioration patterns and predicting future deck conditions. This research is conducted with the latest NBI data for the United States from 1980 to 2020 in a total of 40 years. The dataset of all states except Alaska, District of Columbia, Guam, Hawaii, Puerto Rico, and the Virgin Islands is used.

Data Preprocessing

The raw data contained 215,974 bridge records. The raw data were cleaned by the following steps: (1) remove the bridge without a deck; (2) remove the reconstructed bridge because the focus of the research is to analyze the deterioration without maintenance; (3) remove features only for identification purposes, such as structure number (unique identification of the bridge), county name; (4) drop the data with majority of features missing to improve the performance of the model; (5) group some categorical data. For example, there are only 27 bridges among all highway bridges with aluminum deck structure type. Categories with a small proportion are aggregated into "others" type to reduce the negative impact on model performance; (6) filter the outlier of numerical data, for example, the bridge with zero ADT or with negative age. FHWA's general deck condition ratings are from 0 to 9 and N, in which N represents no application, and 0 to 9 separately indicate failed, "imminent" failure, critical, serious, poor, fair, satisfactory, good, very good, and excellent condition. Moreover, for the better performance of the model, the deck condition should be grouped (*41*). All bridges with deck conditions rating below five were grouped into poor condition, deck condition rated five or six are classified as fair, and all bridges above six were grouped into good condition. This classification method follows the "Pavement and Bridge Condition Performance Measures final rule," published by FHWA in 2017 (*42*). Meanwhile, the bridges under 20 years are grouped into the young bridge category and above 30 years to the old bridge. Finally, the deck condition and bridge age are combined to obtain deck performance. The data of young bridges with poor conditions and old bridges with good conditions are reserved for further analysis. By the data processing of the above step, 152,714 data remained. Then, the categorical nominal variables are converted into ordinal variables for model training. This transformation ensures that the categories are mutually independent and does not generate new variables and sparse matrices like One Hot Encoder. At the end of data preprocessing, the dataset is divided into the training set (80%) and the testing set (20%).

The descriptions and descriptive statistics of the categorical and numerical features are presented in Tables 1 and 2, respectively.

Model Performance

The major challenge for this modeling process is to appropriately handle this heavily imbalanced dataset with less than 5% positive cases—bridges with quickly deteriorating deck conditions—out of the whole dataset. Fortunately, the XGBoost model provided a parameter to increase the weight of the parameters for positive cases during the training. The final model reached an accuracy score of 0.91, F1 score of 0.95, and AUC score of 0.83. For the comparison purpose, this analysis also ran multiple additional commonly used classification algorithms—LightGBM (*43*), gradient boosting decision tree (GBDT) (*44*), and AdaBoost (*44*). The model performance is presented in Tables 3 and 4, and Figure 2. Table 3 shows the general classification model performances. The accuracy scores of all candidate models are above 90%. Comparing these measurements of XGBoost with other models, other models may have higher scores on the accuracy, precision, and F1 score in Table 3, but only the XGBoost model has an above 0.8 AUC score (Figure 2) across all models.

However, for a heavily imbalanced dataset, like the dataset for this study, these common performance measurements for classification models could be misleading. A poorly performed model could also have a high accuracy score with an imbalanced dataset if the model classifies all cases as negative. Therefore, in Table 4, a confusion matrix is also reported. For the positive cases (bridges with fast deteriorating decks), 74% of young bridges with poor deck conditions and 92% of old bridges with good deck conditions are correctly classified by the XGBoost model. For the cases for young bridges with poor deck conditions, which are positive cases in

Table 1. Description and Descriptive Statistics of Categorical Feature

Variable	Description	Levels	Old_Good		Young_Poor	
			Count	Per. (%)	Count	Per. (%)
Owner agency	Type of agency that is the primary owner of the bridge	State highway agency	14,204	44.18	616	37.68
		County highway agency	13,478	41.92	788	48.20
		Other	4,466	13.89	231	14.13
Main design mat	Main kind of material and design of the mat	Concrete	4,297	13.37	241	14.74
		Concrete continuous	3,070	9.55	152	9.30
		Prestressed concrete	12,547	39.03	374	22.87
		Prestressed concrete continuous	3,416	10.63	307	18.78
		Steel	5,308	16.51	474	28.99
		Steel continuous	2,702	8.40	57	3.49
		Wood or timber	808	2.51	30	1.83
Main construction design	Predominant type of construction design	Box beam or girders—multiple	3,519	10.95	500	30.58
		Box beam or girders—single or spread	1,192	3.71	31	1.90
		Channel beam	1,149	3.57	27	1.65
		Others	720	2.24	68	4.16
		Slab	6,694	20.82	212	12.97
		Stringer/multi-beam or girder	16,960	52.76	759	46.42
		Tee beam	1,914	5.95	38	2.32
Approach spans	If existed approach spans	Yes	1,918	5.97	42	2.57
		No	30,230	94.03	1,593	97.43
Deck structure	Predominant type of deck system on the bridge	Concrete cast-in-place	23,317	72.53	1,108	67.77
		Concrete precast panels	5,494	17.09	195	11.93
		Corrugated steel	622	1.93	69	4.22
		Other	1,475	4.59	142	8.69
		Wood or timber	1,240	3.86	121	7.40
Wearing surface	Wearing surface of the bridge deck	Bituminous	7,738	24.07	175	10.70
		Epoxy overlay	487	1.51	4	0.24
		Gravel	976	3.04	36	2.20
		Integral concrete	704	2.19	37	2.26
		Monolithic concrete	17358	53.99	623	38.10
		None	4,253	13.23	667	40.80
		Other	275	0.86	22	1.35
		Other concrete	350	1.09	9	0.55
		Wood or timber	407	1.27	62	3.79
Membrane	Membrane type of the bridge deck	Built-up	312	0.97	44	2.69
		Epoxy	225	0.70	5	0.31
		None	24,378	75.83	1,511	92.42
		Other	6,427	19.99	61	3.73
		Preformed fabric	806	2.51	14	0.86
Deck protection	Protective system of the bridge deck	Epoxy-coated reinforcing	8,679	27.00	280	17.13
		Galvanized reinforcing	20	0.06	43	2.63
		Internally sealed	159	0.49	0	0.00
		None	17,829	55.46	1,253	76.64
		Other	5,452	16.96	58	3.55
		Polymer impregnated	9	0.03	1	0.06

Note: prop. = proportion.

this study setting, the XGBoost model has a significantly higher correctly prediction rate—74%. Table 4 shows that LightGBM, AdaBoost, and GBDT only have 7%, 41%, and 22%, respectively. Therefore, the XGBoost model is adopted because of its superior performance in this study.

Results

Global Feature Performance

Feature importance is a typical measurement to describe the contribution of a feature to the classification task for a tree boosting model. The value of the feature

Table 2. Description and Descriptive Statistics of Numerical Features

Variable	Description	Mean	SD	Min.	Max.
Old bridge with good deck (*n* = 32,148)					
ADT	Average daily traffic	5,658	11,965	10	100,000
Number of spans	Number of spans in the main or major unit	3	2	1	48
Structure length	Length of the structure	168	205	20	3,561
Truck percent of ADT	Percentage of average daily traffic that is truck traffic	7	8	0	98
len_span	Average length of span	64	58	4	992
Structure width	Width of the structure	38	17	4	195
Number of snowfall days	Total snowfall in the current life cycle of bridge	43	40	0	206
Young bridge with poor deck (*n* = 1,635)					
ADT	Average daily traffic	6,080	12,517	10	96,000
Number of spans	Number of spans in the main or major unit	2	2	1	34
Structure length	Length of the structure	163	224	20	2,146
Truck percent of ADT	Percentage of average daily traffic that is truck traffic	5	7	0	99
len_span	Length of the maximum span measured along the centerline of the bridge	75	61	7	942
Structure width	Width of the structure	43	28	8	180
Number of snowfall days	Total snowfall in the current life cycle of bridge	43	39	0	193

Note: SD = standard deviation; Min. = minimum; Max. = maximum.

Table 3. Model Performance Scores (XGBoost model has a better performance)

Model	Accuracy	Precision	F1 score	AUC
LightGBM	0.95	0.95	0.94	0.53
GBDT	0.96	0.95	0.95	0.61
AdaBoost	0.96	0.96	0.96	0.70
XGBoost	0.91	0.95	0.93	**0.83**

Note: AUC = area under the ROC curve; ROC = receiver operating characteristic; LightGBM = Light Gradient Boosting Machine; GBDT = gradient boosting decision tree.

Table 4. Confusion Matrix

	LightGBM				AdaBoost			
	Actual negative	Rate (%)	Actual positive	Rate (%)	Actual negative	Rate (%)	Actual positive	Rate (%)
Predicted negative	6,421	100	5	0	6,386	99	40	1
Predicted positive	304	93	22	**7**	193	59	133	**41**
	GBDT				XGBoost			
	Actual negative	Rate (%)	Actual positive	Rate (%)	Actual negative	Rate (%)	Actual positive	Rate (%)
Predicted negative	6,391	99	35	1	5,923	92	503	8
Predicted positive	253	78	73	**22**	84	26	242	**74**

Note: LightGBM = ; GBDT = gradient boosting decision tree; LightGBM = Light Gradient Boosting Machine.

importance is often considered as the marginal effect of a feature for the model output. The SHAP algorithm uses the mean (|SHAP value|) to measure the feature importance, as shown in Figure 3.

Figure 3 shows that all selected features considerably contribute to model predictions except for the approach span. In other words, these selected features are associated with quickly deteriorating decks. The wearing surface and structure width of the bridge are the two most dominant features affecting the deteriorating rate of the deck conditions. Other features, such as ADT, the number of snowfall days, average length of a span, structure length, main design material, truck percentage of the ADT, predominant type of construction design, deck structure, the number of spans, owner agency, deck protection type, and membrane also show impact on the deck conditions. The approach span has the least impact on the deck condition. These factors are widely accepted

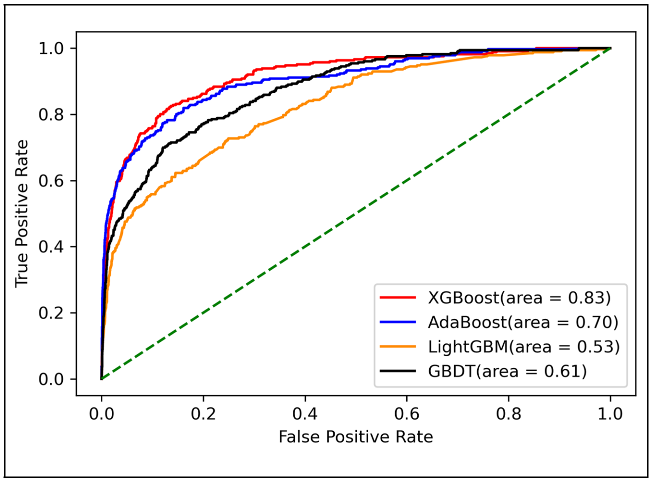

Figure 2. AUC curve of the candidate models.
Note: AUC = area under the ROC curve; ROC = receiver operating characteristic; LightGBM = Light Gradient Boosting Machine; GBDT = gradient boosting decision tree.

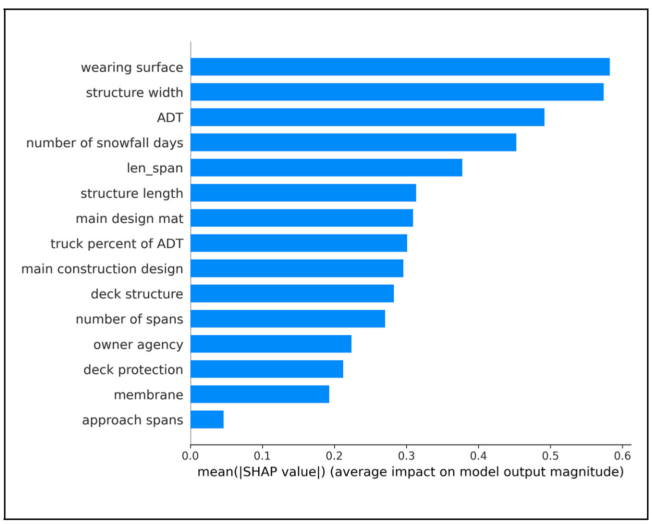

Figure 3. Feature importance based on SHAP values.
Note: ADT = average daily traffic; SHAP = Shapley additive explanation.

and discussed in many previous studies as contributing factors to the deck conditions (*34*, *41*). What makes this finding unique and more interesting is the SHAP framework can provide the feature importance and offer the detailed marginal effects of each feature on the deck conditions. More details about how these features affect the deck conditions will be discussed in the following sections.

Feature Importance of Numerical Features

The SHAP algorithm also provides a detailed feature importance plot for continuous features, which is also introduced as local interpretability in the original SHAP paper (*40*). The feature importance bar in Figure 4 consists of points. Each point is an observation in the original dataset. The color of the point indicates feature value—red is high, and blue is low. The horizontal position of the point on the x-axis indicates the SHAP value of that feature for that particular observation. Positive and higher SHAP value means the prediction leaning more to predict the bridge as a relatively young bridge with poor deck conditions, and negative and lower SHAP value represents the bridge is more likely to be an old bridge with good deck condition. To avoid incorrectly interpreting the plot, it is important to note that some features may present a clear trend: the feature value generally linearly affects the prediction results, such as structure width and the average length of a span. Some features, such as structure length, may show mixed trends, which are not linear and require future analysis. Features showing mixed trends do not suggest the impact of the feature on the deck condition is totally random. There are interactive effects among different features.

A wider deck surface increases the probability of quickly deteriorating deck conditions for relatively younger bridges for structure width. Bridges with a wider structure width often have more lanes and require more supports in the lateral direction. More lanes also indicate more traffic. These factors associated with the wider width may cause fast deterioration for young bridges. For the average length of the span, the bar clearly shows that a longer average length of the span leads to quickly deteriorating deck conditions. In general, bridges with more spans tend to have better performance of the deck condition.

Individual Feature's Effect

The partial dependence plot (PDP) is a critical approach that collectively shows a feature value's corresponding SHAP value. PDP provides a visual way to understand how the changing values of a feature could affect the model output through SHAP values. In other words, the plot shows how each feature affects the deck condition. Figures 5 to 8 present the PDPs for eight selected features, including four categorical features (climate region, deck structure, wearing surface, deck protection) and four numerical features (number of spans, average length of a span, ADT, truck percentage of ADT). The x-axis and y-axis (on the left-hand side) of the PDP represent the feature value and the corresponding SHAP value of a particular feature value. A positive and higher SHAP value means the deck condition is more likely to be classified as a quickly deteriorating condition. On the right-hand side of the y-axis, the color bar indicates the value of another feature. Each point (individual observation)

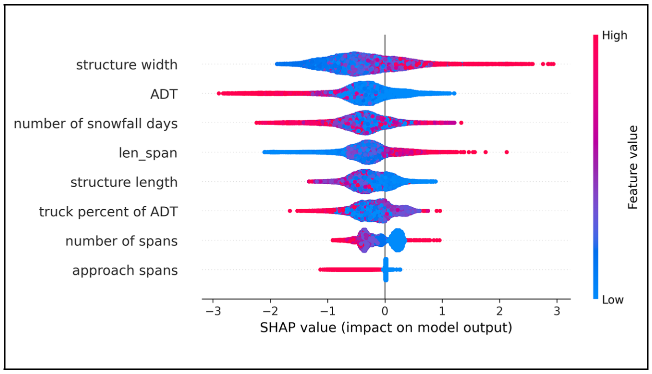

Figure 4. Local interpretability of the feature importance.
Note: ADT = average daily traffic; SHAP = Shapley additive explanation.

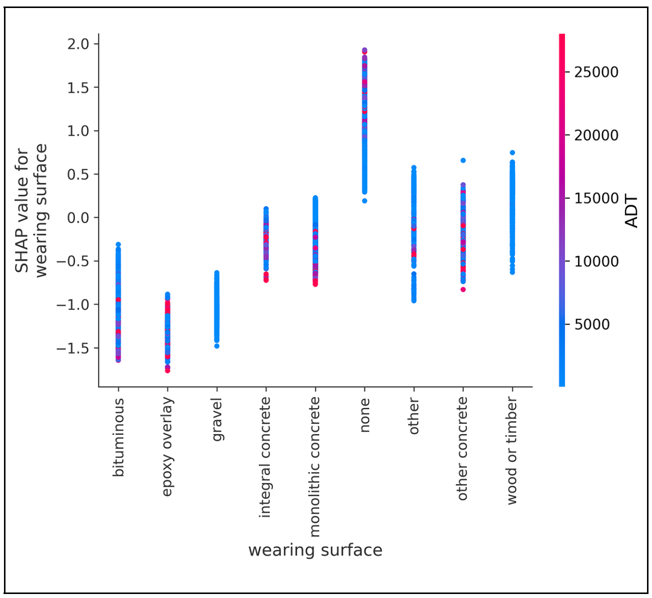

Figure 5. Partial dependence plot of wearing surface.
Note: ADT = average daily traffic; SHAP = Shapley additive explanation.

in the plot is colored by the value of this feature, which could offer additional value for the interpretation. Details about how the changing right-hand feature value would help the interpretation will be discussed in later sections

Wearing Surface. The wearing surface is a layer over the bridge deck to provide a smooth surface for the traffic and protect the bridge against abrasion from vehicles (*45*). In Figure 5, the only category of the wearing surface feature dominantly associated with the quickly deteriorating deck condition is without wearing surface. This finding proves the importance of having a wearing surface. Some 89% of these "non" wearing surface (bridges without a wearing surface) bridges have a "concrete cast-in-place" deck structure. Nevertheless, across all types of

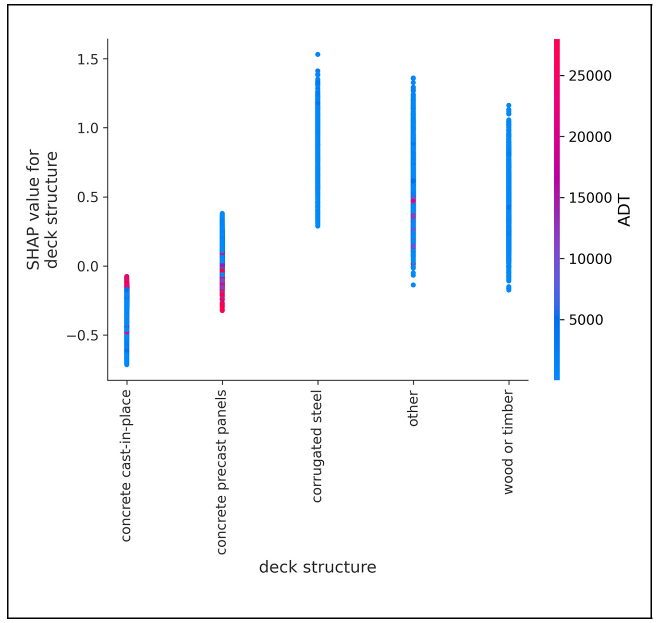

Figure 6. Partial dependence plot of the deck structure.
Note: ADT = average daily traffic; SHAP = Shapley additive explanation.

wearing surface, bituminous, epoxy overlay, and gravel are three types of wearing surface with better performance than others. From the right-hand side y-axis, the bridges with gravel decks often have low traffic. The relatively low usage of the bridge may partly explain the good performance of decks with this wearing surface. Moreover, decks with integral concrete or monolithic concrete type of wearing surfaces have decent performance on protecting the deck condition.

Deck Structure. Figure 6 shows the effects of deck structure on the deck conditions. The concrete cast-in-place structure is highly associated with the old bridge still having a good deck condition. The concrete cast-in-place structure has no beams under the deck. This structure uses embedded reinforcing steel and thick concrete to carry the loads (*46*). This type of deck structure is relatively maintenance-free and has better performance than other structure types. The corrugated steel structure is also commonly used in bridges across the U.S. This type of structure is easy to install and lightweight, which could potentially increase the load that a bridge can support. However, the corrugated steel structure is highly associated with the young bridge with a quickly deteriorating deck condition compared with all other deck types. Except for the concrete cast-in-place structure and the corrugated steel structure, the associations between the deck condition and other deck structures are less dominant.

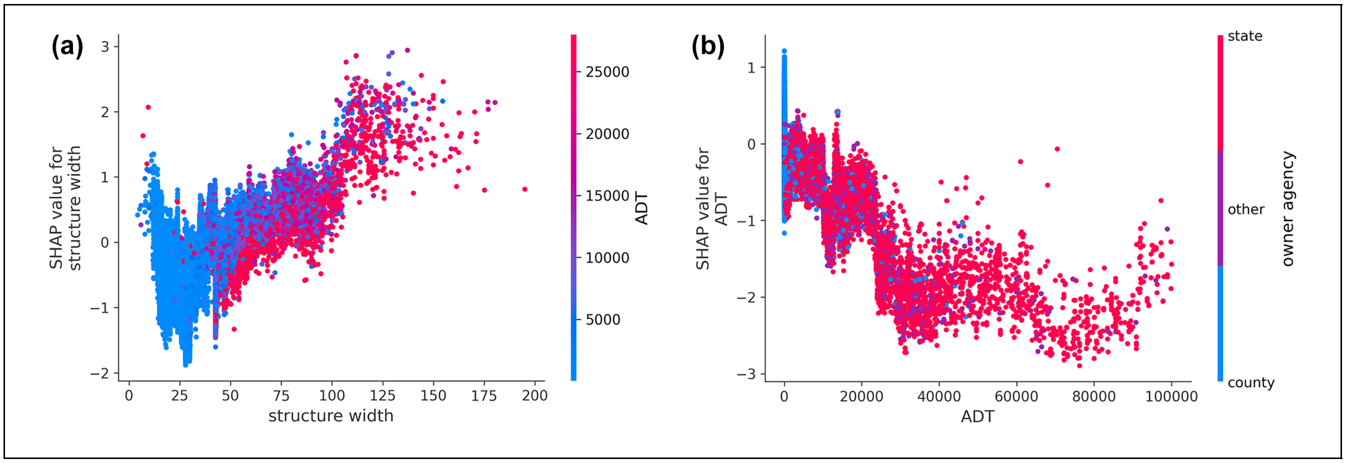

Figure 7. Partial dependence plots of (*a*) structure width and (*b*) average daily traffic (ADT).
Note: SHAP = Shapley additive explanation.

Structure Width and ADT. Bridge structure width and ADT are the second and third most dominant features associated with deck conditions. Figure 7, *a* and *b*, indicates the marginal effects of the structure width and ADT on the deck conditions. Figure 7*a* illustrates that a bridge's deck condition is more likely to be classified as quickly deteriorating as the width of the bridge becomes wider. Wider bridges normally require more supports to distribute the weight and more joints to accommodate the shrinkage and temperature variation. At the same time, more supports and joints make the deck of a bridge more vulnerable.

Meanwhile, a wider bridge could also mean more lanes and higher traffic volume. The color bar on the right side of Figure 7*a* represents the ADT value. As the ADT goes up, the color of individual points changes from blue to red. The figure shows that as the structure width goes up, the value of ADT increases. Thus, a higher ADT may contribute to the quickly deteriorating deck condition. However, Figure 7*b* disagrees with this speculation. First, this figure shows that the effects of ADT on deck conditions are not linear. Second, the general trend is that the bridge with a higher ADT has less chance to have a quickly deteriorating deck condition. The right-hand sidebar also indicates that bridges with higher ADT are mostly owned by state highway agencies. In reality, a higher traffic volume could cause more damage to the deck of a bridge. However, because of the bridges' importance in connecting the road networks, bridges with high traffic volume attract more attention and funding and are often better maintained by the state highway agencies.

Average Length of a Span and Number of Spans. Figure 8*a* shows the effect of the average length of a span on the deck conditions, and Figure 7*b* shows the effects of the number of spans on the deck conditions. Two features show opposite effects on the deck conditions as their values increase. For the average length of a span, a long span has negative impacts on the deck condition.

Figure 8*a* suggests that the bridge with an average length of a span longer than 200 ft is more likely to have a quickly deteriorating deck condition. Multiple previous studies mentioned that long-span bridges could compromise the decks' durability because of the vibration mechanisms (*6*, *47*, *48*). As mentioned in the data description section, for the number of spans, among all selected bridges for this analysis, about 80% of bridges only have one or two spans. However, the overall trend remains: an increasing number of spans positively affects the deck conditions. More spans may help the bridge structure evenly distribute the loads and generate less impact on the deck condition. Figure 8*b* also presents a sudden increase in the chance of quickly deteriorating deck condition when the number of spans is over about 20. Out of 33,783 bridges in this study, there are only 61 bridges with over 20 spans. This tiny fraction of bridges may require further investigation on this particular issue.

Truck Percentage of ADT. Compared with passenger vehicles, which are the majority in the traffic, trucks have much higher impacts on the road surface and deck conditions.

There are multiple interesting findings in this PDP in Figure 9. First, for bridges with relatively low truck percentages (less than about 8%), the influences of low truck percentages on the deck condition are limited. However, there still exists a trend, the likelihood of being classified as quickly deteriorating decks increases when the truck percentage goes up. Up to about 8%, the bridge is more

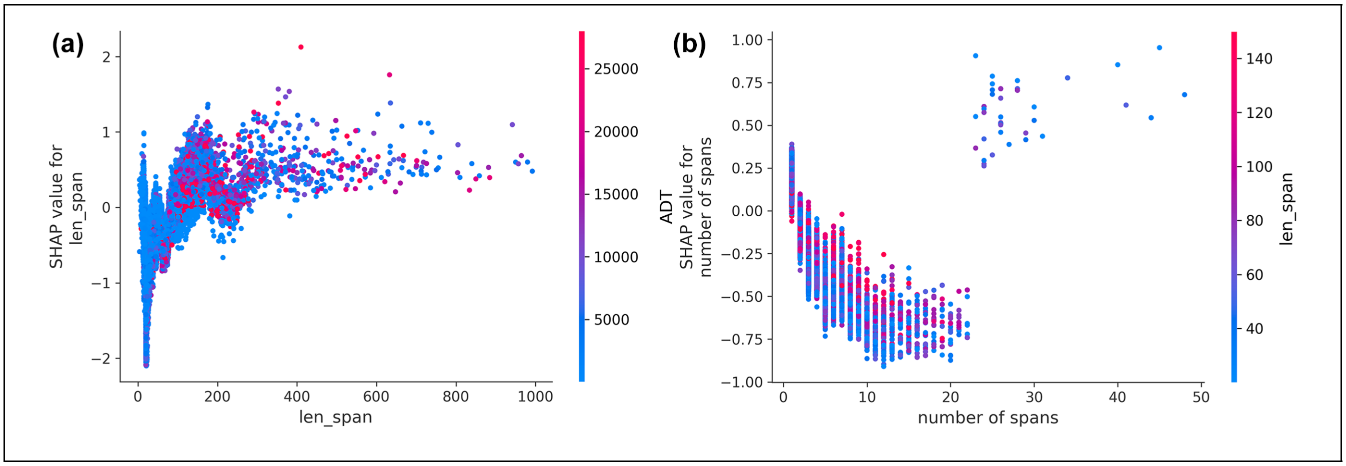

Figure 8. Partial dependence plots of (*a*) average length of a span and (*b*) number of spans.
Note: ADT = average daily traffic; SHAP = Shapley additive explanation.

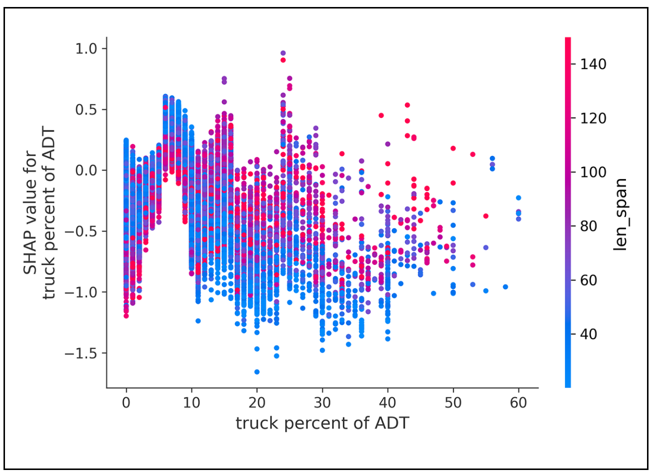

Figure 9. Partial dependence plot of truck percentage of average daily traffic (ADT).
Note: SHAP = Shapley additive explanation.

likely to have quickly deteriorating decks. Interestingly, this trend quickly drops, and the majority of bridges with a relatively high truck percentage are less likely to have quickly deteriorating decks. There are two possible explanations. First, although a higher truck percentage does not always imply a higher ADT, two features could be concurrent in many road segments. As discussed above, bridges with a higher ADT often are managed by state highway agencies and are eligible for receiving more funding for maintenance. Second, there are additional sources for supporting the roads, bridges with high truck traffic, such as National Highway Freight Network (NHFN) (*49*). Another finding is that, for a bridge with a relatively high truck percentage (higher than 8%), the bridge is more likely to have a quickly deteriorating deck when the span length is long (see points in the green circle). This finding shows that trucks could result in even more damage to bridges with long spans because of their heavy weights.

Interaction Effect

The contribution of a feature to the final classification consists of two parts: the main effect and the interaction effect. The main effects of the features were introduced in the previous section. SHAP can also calculate interaction values among two features. After analyzing the interaction effects among all features, the results indicate that ADT has apparent interaction effects with the average span length.

Interaction Effect Between the ADT and Average Length of a Span. Figure 10 shows the patterns of the interaction effect for ADT and the average span length. For bridges with relatively short spans (blue color dots), the interaction values consistently gather around zero SHAP value as ADT increases, which indicates the interaction effect between ADT and average short span length has no clear impact on the deck deterioration. For bridges with longer spans (red color dots), the interaction effect increases the odds of a bridge having a fast deteriorating deck condition when the ADT is less than about 30,000. However, as the ADT increases, the interaction effect reduces the probability of a bridge having a fast deteriorating deck. This does not suggest that longer spans could better maintain the deck condition with heavier traffic than short spans. Considering the results and discussions for Figures 7*b* and 8*a*, what data-driven results presented in Figure 9 show is that, in the real world, bridges with more traffic volume could have more funding resources and higher maintenance standards to maintain a better

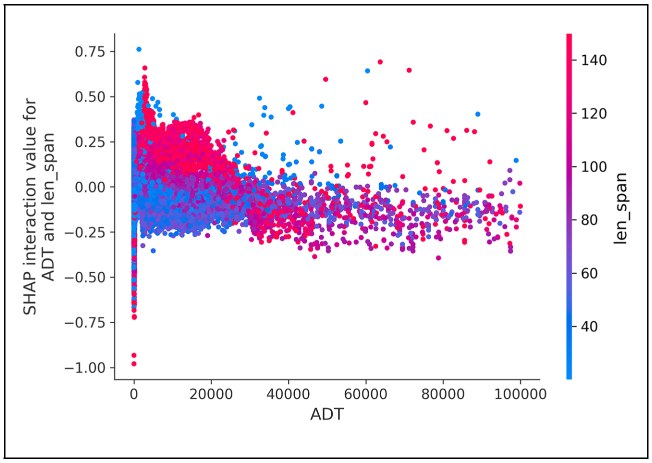

Figure 10. Interaction effect between average daily traffic (ADT) and the average length of a span.
Note: SHAP = Shapley additive explanation.

deck condition. Therefore, bridges with more traffic volume could have higher odds of having good deck conditions for long spans.

Findings

The major findings are listed below:

- Wearing surface, structure width, ADT, number of snow days, span length, truck percentage of traffic, and so forth, are associated with fast deck deterioration.
- Having a wearing surface is critical for protecting the bridge deck.
- Out of multiple wearing surface types listed in the dataset, bituminous and epoxy overlay wearing surface types are highly associated with relatively old bridges with good deck conditions.
- For deck structure, the concrete cast-in-place type has the best performance on deck conditions, and the corrugated steel type is highly associated with quickly deteriorating decks.
- A wider bridge structure increases the chance of having a quickly deteriorating deck. A wider bridge often requires more supports and joints to distribute the weight and handle the temperature variation, which may hinder the deck performance.
- Bridges with a higher ADT have less chance to have quickly deteriorating decks. Bridges with higher ADTs often are managed by state highway agencies and possibly could receive more funding for maintenance.
- Long-span bridges lead to quickly deteriorating decks, and more spans for a bridge increase the stability and performance of the deck.
- For a bridge with a relatively low truck percentage of ADT, deck condition is less likely to suffer quickly deteriorating, but the likelihood increases as the truck percentage increases. Interestingly, for a bridge with a relatively high truck percentage, the likelihood of having a quickly deteriorating deck drops, and this trend is maintained as the percentage continuously goes up. There are programs like NHFN that support and locate more resources for these bridges with high truck volumes to keep these decks in good condition.
- The interaction analysis shows that the long span length has a negative impact on deck conditions with bridges with a relatively small ADT. This negative impact decreases while the ADT increases, which suggests that bridges with a higher ADT may receive more maintenances or funding resources.

Conclusion

This study investigates the associations between the bridges with quickly deteriorating decks and deck condition-related factors through an interpretable machine learning framework. Data on all bridges available in the NBI and built in 40 years are collected. The bridges under 20 years old with poor or fair deck conditions are considered as young bridges with quickly deteriorating decks, and bridges older than 30 years old and with good deck conditions are considered as old bridges with good deck conditions. There are 33,783 bridges that fit the criteria and are analyzed. The analysis is performed in two steps. The first step is to train the predictive classification model. The research question has been formulated as a binary classification task, and the predictive classification model is trained by the XGBoost model. Second, the trained models are applied to the SHAP interpretable machine learning framework, and results are discussed and summarized.

The results reveal a list of features associated with quickly deteriorating decks, such as wearing surface, structure width, and so forth. The bituminous and epoxy overlay wearing surface types are found to have the best performance on protecting the decks. The analysis also demonstrates corrugated steel deck structure, wide bridge structure, and long span are highly associated with quickly deteriorating decks. Bridges with a relatively low ADT or truck percentage of ADT are more likely to have quickly deteriorating bridges. The reason behind this interesting finding could be that although the ADT or truck percentage of ADT is relatively low, the traffic volume or truck volume is not low enough to neglect their impacts on the decks, but, unfortunately, these volumes are not high enough to be eligible for receiving additional funding resources for maintenance.

There are also some limitations worth mentioning. First, for all bridges built in the past 40 years (1980–2021), the authors defined the less-than-20 years-old bridge with poor or fair deck conditions as quickly deteriorating decks. For bridges built in the last 20 years, there are very few bridges with poor deck conditions. To ensure an adequate training data size, authors include bridges with fair deck conditions. Bridges built in the last 20 years and with fair deck conditions are not desirable. This definition is defensible but still needs further study to support it. Second, some relevant factors are excluded from the analysis because of their correlations with other factors, such as climate region, which may correlate with the number of snow days. Further investigation is needed on these excluded factors. Third, quickly deteriorating deck conditions could be affected by multiple factors rather than a single individual factor. For a single factor, the overall performance across bridges may be excellent, but it is entirely possible that the combination of this factor with others may lead to the fast deterioration of a deck. Such combination effects require further study.

Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: X. Kong, Z. Li, Y. Zhang; data collection: X. Kong, Z. Li; analysis and interpretation of results: X. Kong, Z. Li. Y. Zhang, S. Das; draft manuscript preparation: X. Kong, Z. Li. All authors reviewed the results and approved the final version of the manuscript.

Declaration of Conflicting Interests

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