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Enhancing Bridge Management: A Data-driven Approach for Accurate Forecasting of Concrete Bridge Condition

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Abstract:

Highway bridges are vital components of infrastructure systems that support effective vehicle flow throughout the transportation network. Nevertheless, several factors, including the age of the bridge, operational characteristics, and exposure to the climate threaten the continuous function of such bridges. Because of this, it may be challenging to confidently anticipate the condition of bridges and prioritize needed maintenance tasks. In this article, we suggest a smart data-driven methodology for forecasting the condition of bridges based on a range of structural and operational aspects. In addition, several climatic factors were considered to assess the impact of environmental exposure on bridge conditions.

Different machine learning algorithms including neutral network, support vectors machine, random forest, and others were trained utilizing historical bridge inspections in the U.S. Feature engineering and hyperparameter tuning techniques was used to identify the factors that have the most influence on the condition. With a mean relative error of 3.8%, GBT produced the most promising results. Additionally, the research demonstrated the predictive significance of some climatic parameters, particularly the freezing index. The developed model provides an accurate and timely assessment of their condition which can be leveraged to prioritize maintenance and renewal activities.

Keywords: Bridge management, condition prediction, machine learning, data-driven modeling, climatic factors.

1. Introduction

Highway bridges are essential for the safe and efficient movement of people and goods. Nonetheless, they face several challenges, including urbanization, deterioration, aging, and budget constraints. These challenges are compounded by the need to cope with natural disasters, increased traffic, aging, and environmental constraints. In the United States, for example, 42% of bridges were built before 1980 and 7.5% are structurally deficient according (ASCE 2021). To make it worse, climate change is having a significant impact on the transportation sector, with annual direct damages to road and rail assets estimated to be between 3.1 and 22 billion dollars (Liu et al. 2022). This damage is caused by a variety of factors, including extreme weather events, sea level rise, and changes in precipitation and temperature patterns. This necessitates a focus on asset management programs to ensure the long-term sustainability of bridges against this wide spectrum of disruptive sources. The first keystone in establishing such plans is to assess the condition of highway bridges. Such assessment can assist in determining the optimal plans for capital renewal projects and restoration activities following widespread hazards.

This research aims to investigate the use of machine learning algorithms to assess the condition of highway bridges, considering the impact of climate factors. The study uses two datasets: the NBI database, which contains information on the condition of bridges in the United States, and the LTPP climate dataset, which contains information on weather stations in different location across the country. The research team developed several models to estimate the condition of highway bridges and identified the key influential highlighting the climatic factors impact on the condition of highway bridges.

2. Literature review

Condition assessment is essential for transportation agencies to accurately describe the extent of bridge deterioration. Several research efforts have presented methods to estimate the condition of highway bridges. Most of these attempts have focused on structural factors, such as the condition rating of various bridge components and the overall load-carrying capacity. For example, Amiri et al. (2019) presented an approach for ranking maintenance actions of highway bridges considering both structural and financial aspects. Multi-criteria decision-making techniques, such as the Analytic Hierarchy Process (AHP) and the Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) were investigated to determine the relative importance of the considered factors. Prior to this, Alsharqawi et al. (2018) used Quality Function Deployment (QFD) to analyze several faults, including corrosion delamination, spalling, and fractures, to evaluate the condition of concrete bridge decks. In a different approach, Abu Dabous et al. (2017) evaluated the condition of bridge decks by creating an integrated model that used ground penetrating radar and infrared thermography maps. The ground penetrating radar and infrared thermography threshold values used in the created model were arbitrarily determined for each individual example. Dinh and Zayed (2016) employed fuzzy theory to develop computerized software that estimates the bridge deck corrosiveness index that takes into consideration the fuzziness associated with the expert opinions.

It is evident, in view of previous studies, that the accuracy and comprehensiveness of prior condition assessment of concrete bridges can be improved by addressing several issues that should have been considered. For instance, there is still a need for a single integrated model that can accurately represent the multidimensional nature of bridge condition assessment. Global warming is set to accelerate the structural deterioration of bridges by 31%, decrease their service life by 15 years (Bastisdas-Arteaga et al., 2013), and increase the maintenance and repair costs (Ekolu 2020). Nonetheless, the influence of climatic conditions on the properties of concrete bridge decks was investigated by only a few models. It is necessary to develop a comprehensive model that takes operational, structural, and climatic elements into account. It would be beneficial to assess the respective capabilities of more advanced algorithms such as deep learning, bagging, and boosting, and others. This would expand the knowledge about the appropriateness and efficacy of machine learning methods for forecasting bridge conditions while taking the climatic conditions into account.

3. Methodology

Figure 1 depicts a flowchart methodology followed to fulfill the objective of this study. After reviewing the relevant literature, the study proceeds in the data acquisition stage. In this phase data about structural, operational, and climatic influential factors were gathered as well as the observed condition ratings of highway bridges. Data pre-processing protocol then started to prepare the data for model calibration. Next, feature engineering is carried out to determine the most influential factors and reduce the model's complexity. Several data-driven models were then calibrated based on machine learning algorithms, with each model's hyperparameters automatically tuned through a cross-validation procedure to improve the model's performance. Finally, the best performing model was determined exploiting several performance measures. Underlying concepts and mathematical formulation are detailed in the subsequent section.

3.1.Data collection and pre-processing

The data was extracted from NBI database, Long-Term Pavement Performance (LTPP) climate tool, both controlled by Federal Highway Administration (FHWA 1995). The bridge dataset includes information about the location, geometrical aspects, structural elements, construction parameters, and conditions of the bridge, among more than 120 parameters. Furthermore, historical conditions from the years 2021 and 2020 have also been extracted. The Federal Highway Administration exploits a 10-point rating system ranging from 0-9 to evaluate concrete bridge decks condition. In this inventory, condition rating 9 represents the highest condition or the least maintenance requirement, and vice versa.

The LTPP dataset that was acquired contains details on the locations of several weather stations as well as details on climatic factors like precipitation, temperature, freeze and thaw, and evaporation. Based on the locations of the bridges and weather stations, two datasets were combined. To guarantee that each bridge would be paired with the closest weather station, the weather stations in the surrounding states of the state under study were also checked.

Before constructing the various machine learning models, several data preparation tasks were carried out to make sure the dataset has been cleaned and translated into the proper format for prediction. The dataset was first cleared of incorrectly coded, redundant, and missing attributes. Any data point that had the value NA, not applicable, was similarly eliminated from the database. Major rehabilitation renewal efforts would normally change the deteriorating behavior of concrete bridge decks. Bridges that had undergone such measures were excluded. When a bridge is rebuilt, its age is determined using the new reconstruction year.

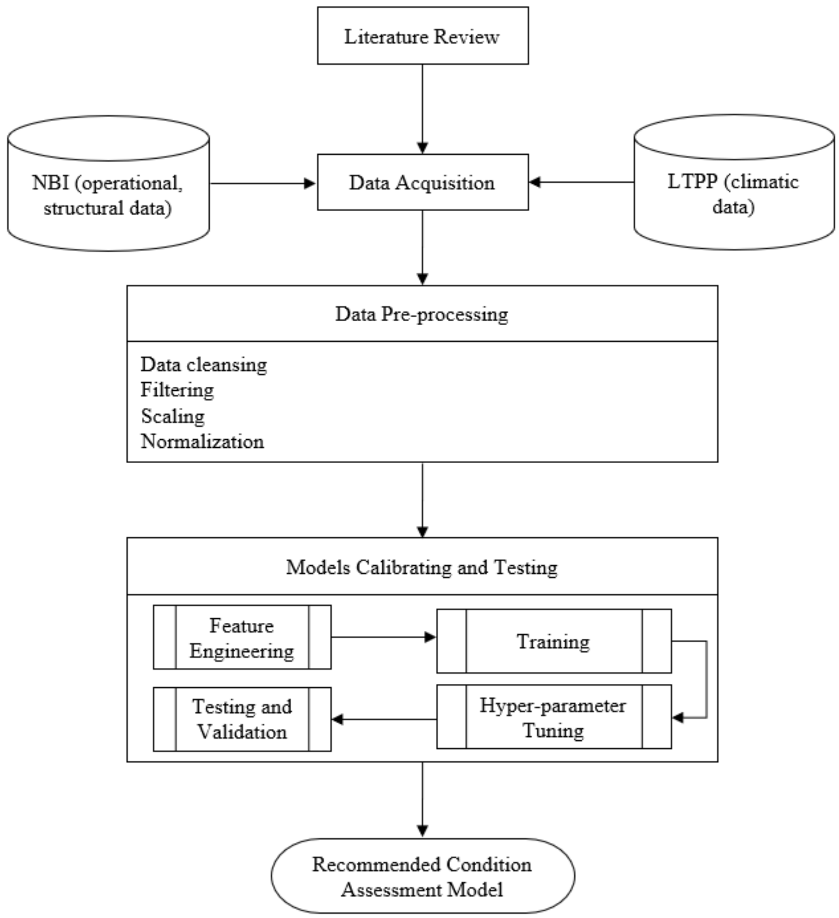

Figure 1. Methodology Framework

3.2.Model calibration and testing

In this phase, the data was first split into two main classes with percentages of 90% and 10% for training and validation and testing, respectively. Cross-validation is used to further divide the early portion of the data for model-building process into training and validation sets. By lowering the bias in selecting the validation set, cross-validation helps to provide a more accurate assessment of the prediction accuracy and prevents overfitting. During cross-validation, the dataset is separated into K groups and then shuffled. The K^{th} group is left for validation after fitting and training the prediction model using K-1 groups. A new group is then held for validation while the remaining ones are used for training as the operation is iteratively repeated. Next, each iteration's average performance is exploited to calculate performance. Through an optimization procedure that automatically modifies the settings of the prediction algorithms, the cross-validation classification error will be reduced. Testing set,10% of the data, that neither the training nor the validation processes have seen will be used in the final accuracy assessment. This holdout collection is essential for generalization to ensure that tested prediction models perform well on fresh datasets for upcoming applications.

Hyperparameter tuning is employed in this study during the training phase. Hyperparameters are predetermined settings that have a large impact on the performance of the model though cannot be discovered by data-driven learning. Grid search was used in this work to automatically explore possible combinations of hyperparameter values for the algorithms under investigation. Grid search allowed finding the ideal setup that enhances the performance of the model by thoroughly scanning the predefined hyperparameter space.

Feature engineering plays a crucial role in enhancing the model's performance. Feature selection involves identifying and retaining the most relevant features while eliminating irrelevant or redundant ones. By doing so, we ensured that the model focuses on the most informative aspects of the data, reducing noise and preventing overfitting. In this study, 20 factors out of the 120 available on the original database were selected to build the models. This was done based on their relevance to the deterioration of highway bridges and overall impact on the models' accuracy. Different models have been developed in this work, based on naïve base, support vector machines, decision trees, random forests, gradient-boosted trees, deep learning, and generalized linear models. These models were picked because they are frequently used in asset management systems and can mimic complex interactions, such as those influencing the deterioration of highway bridges (Assad and Bouferguene 2022). The constructed prediction models are briefly discussed below followed by a comparison of each model's accuracy.

Generalized Linear Model (GLM)

With this strategy, linear regression may be generalized to include any exponential family distribution instead of just the normal distribution for the dependent variable. This exponential family includes several probability distributions, such as the normal, binomial, gamma, and others. Equation (1) provides a link function that can be used to relate the mean value of the dependent variable distribution to the independent variables. A penalty term is also added to control the error variance and lessen the variability of the projected values. To select the best family distribution and link function, a parameter tuning optimization is carried out. The best GLM model used in this study makes use of the logarithmic link function and Gaussian family distributions.

$$\mu = E(Y|X) = g^{-1}(X\beta) \tag{1}$$

Where $E(Y|X)$ is the mean value of the dependent variable Y conditioned on X, $X\beta$ is a linear combination of the dependent variables and unknown weighting coefficients, and g is the link function.

Naïve Bayes (NB)

NB serves as a high-bias, low-variance algorithm that may produce useful models with a small amount of data and at a low computational cost. The core tenet of Naive Bayes is that each attribute's value is independent of all other attribute values, given the value of the class. This assumption may be theoretically erroneous and naive, but numerous real-world applications show that the NB algorithm typically works well. The calculations necessary to generate the NB probability model are considerably simplified by the independence requirement. To complete the probability model, the conditional probability distributions for each Attribute, given the class, must be presupposed. The attribute data was modelled using Gaussian probability densities.

Deep Learning (DL)

A more complex version of neural networks with several processing layers, each capable of difficult nonlinear transformations, is shown by DL architecture. DL networks, in contrast to standard ANNs, can learn from extremely complicated functions of the raw data by automatically extracting significant features at multiple tiers. The regularization method is used to limit the probability of overfitting by introducing a term of penalization to the cost function. In this study, a three-layer DL network with a total of 10 epochs and a Rectifier linear unit activation function yielded the best accuracy.

Table 1. Bridge deck attributes list

Attribute	Brief Description	Data Type
Age	The age of the bridge	Numerical
Functional class	The functional classification of the bridge	Categorical
Traffic lanes	The number of lanes being carried.	Numerical
ADT	The average daily traffic volume.	Numerical
Status	Actual operational status of the structure	Categorical
Service	The type of service on the bridge	Categorical
Structure type	The predominant type of construction	Categorical
Max span length	The length of the maximum span measured along the centerline of the bridge	Numerical
Structure length	The length of the structure;	Numerical
Left and right curb	The width of the left curb or sidewalk	Numerical
Deck width	The out-to-out width of the deck	Numerical
Operating rating	The absolute maximum permissible load	Numerical
Inventory rating	The load level	Numerical
Structural evaluation	The structure evaluation of the bridge	Ordinal
Truck ADT	The average daily traffic associated to truck	Numerical
Deck area	The area of the bridge deck	Numerical
Bridge condition 21	Bridge condition as observed in year 2021	Categorical
Temperature average	Average of the daily mean air temperatures.	Numerical
Freeze index	Summation of difference between 0 degrees Celsius and mean daily air temperature.	Numerical
Freeze thaw	Number of days in the year when the maximum air temperature is greater than 0 degrees Celsius and minimum air temperature is less than 0 degrees Celsius on the same day.	Numerical

Support Vector Machine (SVM)

SVM is a supervised learning technique built on statistical theory that may be used for tasks such as classification. Typically, the SVM algorithm uses a hyperplane, a higher-dimensional space, to map and classify input data into a certain category. By mapping in a higher-dimensional space, it becomes simpler to separate datasets that are challenging to separate in the original space. To ensure computational viability, the mapping technique includes developing a kernel function using the variables suited for the current issue. The most effective SVM in the current investigation uses a radial kernel type with a C value of 1000 and a kernel gamma of 5.0.

Decision Tree (DT)

DT is a predictive learning technique based on the divide-and-conquer approach. DT provides straightforward technique that can be used for prediction and classification tasks (Velasco et al. 2021). To estimate a target variable and divide the prediction space into different areas, several predictive rules are coupled in a hierarchical, tree-like form. The procedure is separated into decision nodes depending on predictor qualities, starting with a root node that utilizes all the initial attributes. At each branch, the process is repeated until no further classification is possible. The nodes at which the procedure for splitting is completed are called leaves. The decision tree model in this application with the highest accuracy has a maximum depth of 25.

Random Forest (RF)

RF is used to address overfitting, a serious problem with decision trees (Assad and Bouferguene 2022). RF is a variant of traditional DTs that divides the initial data set into several subgroups using the bootstrap method. Using randomly selected decision factors, a separate tree is then constructed from each subgroup using the optimal split criterion. Finally, to provide more precise forecasts, these trees are bagged and aggregated. The bagging technique only applies a greedy algorithm to randomly chosen portions of the initial predictors at each split, reducing the correlation between different trees. The random forest model in this study that produces the best results has a maximum depth of 10 and 100 trees.

Gradient Boosted Algorithm (GBT)

Boosting methods combine numerous weak models to produce a robust model, which improves prediction accuracy and prevents overfitting by optimizing a differentiable loss function (Velasco et al. 2021). The training starts with a single tree that represents a weak learner that will be continuously improved. After each iteration, the tree is changed based on the previous forecast. The parameters optimization is guided by the gradient and the second-order derivative of the loss function. The current investigation produced a 150-tree GBT model with a maximum depth of 7 and a learning rate of 10%.

To evaluate each model's performance, accuracy was calculated as illustrated below:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{2}$$

Where TP, TN, FP, and FN mean true positive, true negative, false positive and false negative, respectively.

4. Results and Discussion

To direct the feature engineering process, the correlations between the considered factors were investigated. As previously mentioned, feature engineering entails creating new features or modifying current ones to enhance the performance of a machine learning model. One aspect of feature engineering is analyzing the correlations between factors, which is typically accomplished with the aid of a correlation matrix. The correlation matrix can be used as a guide for choosing features or managing correlated features by quantifying the relationships between features.

The correlation coefficients between the considered attributes, factor, are depicted in a square matrix. The Pearson correlation coefficient was used in this study to assess the significance and direction of the link between two variables. Its value can be anything between -1 and 1, with -1 denoting a perfect negative correlation, 1 denoting a perfect positive correlation, and 0 denoting no correlation at all. The heat map of the correlation between the attribute variables in this study is shown in Figure 2. A stronger association is denoted by a deeper hue, while a weaker or absent correlation is denoted by a lighter color. One attribute is retained from each pair of factors with the same correlation behavior, coefficient of more than 0.5, with other attributes to prevent redundancy. On the other hand, some attributes might exclusively exhibit high correlation coefficients among each other which implies a degree of correlation. Nonetheless, these factors are kept in the analysis as they inherit vital information to the deterioration problem with no sufficient statistical evidence of co-linearity. In addition, various regularization techniques were employed within the utilized modeling algorithms to address this issue to avoid overfitting and facilitate generalizing the obtained results with a higher confidence level.

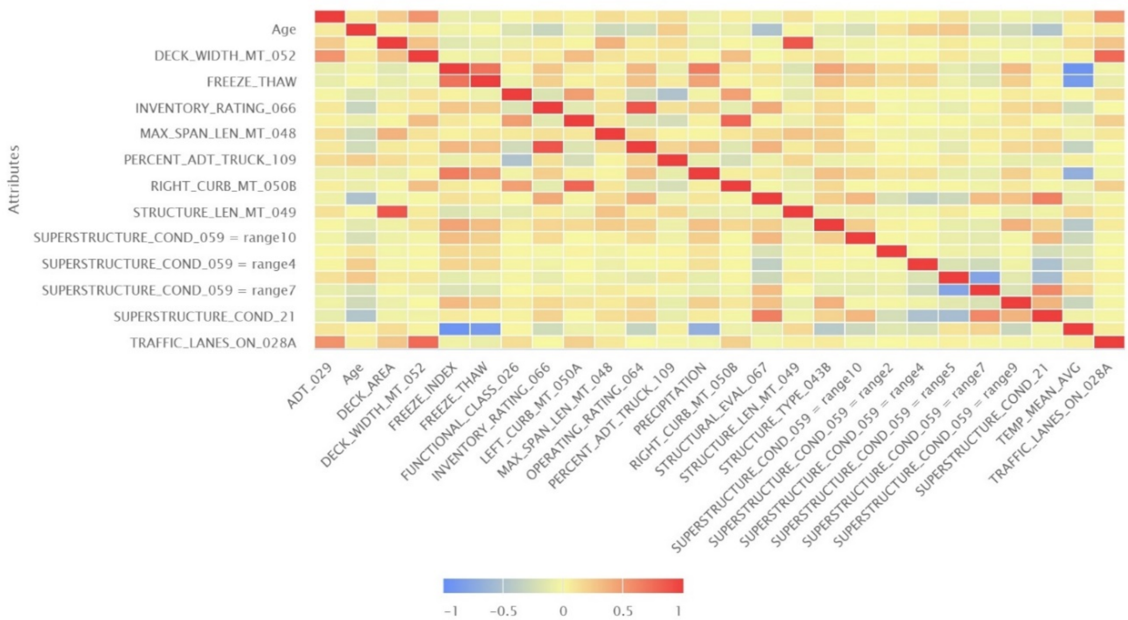

Figure 2. Correlation heat map of input attributes

The accuracy of the constructed condition prediction models is shown in Table 2 as performance indicators. The results show that the GBT model surpasses 96% accuracy, which is the highest obtained. The GBT model is extremely desirable due to its remarkable accuracy, particularly for decision-makers looking to embrace and include it in their asset management plans for highway bridges. The GBT model has the additional advantage of not offering a black box model, which makes it simpler to understand and use. It is also important to note that Table 2 displays the standard deviation of accuracy for all generated models which is typically around1% or less. The consistency and dependability of the forecasts were ensured by such low standard deviation values. The GBT model is ultimately the best option based on the results due to its remarkable accuracy, transparency, and stability.

A measure of importance of each input attribute used in the GBT-based condition prediction model is shown in Figure 3. By indicating the predictive significance of each factor, this measure provides additional insights into the condition assessment of highway bridges. The relative weights in Figure 3 show how each feature contributed to the final bridge condition rating. The highest weight indicates that the prior condition of the bridge is very important in determining the current condition. Data from the past condition inspection is very insightful and significantly affects the prediction. Additionally, the structural capacity of the bridge has a significant impact on the condition rating of the bridge since it indicates the load-bearing capacity and overall strength, which controls the failure mechanism.

Table 2. Accuracy of the developed models

Model	Accuracy	Standard Deviation
NB	88.3%	±0.5%
GLM	94.3%	±0.5%
DL	94.8%	±0.8%
DT	91.8%	±1.1%
RF	92.5%	±1.0%
GBT	96.2%	±0.9%
SVM	54.22%	±1.59%

Our analysis shows that the weather and exposure to subfreezing temperatures have a significant impact on the condition of bridges. When the mean daily air temperature is less than 0 degrees Celsius, the LTPP defines the freezing index attribute as the total of the difference between 0 degrees Celsius and mean daily air temperature. Temperature changes can cause the bridge material to expand and compress, which has a direct impact on its resilience and structural integrity.

In addition, precipitation—including snowfall or rain—has a tangible effect on the condition of the bridge. Corrosion, erosion, or other sorts of damage that affect the bridge's condition might be brought on by excessive moisture or constant exposure to water. These findings shed important light on how the condition rating of highway bridges varies depending on climatic variables. Hence, it is crucial to incorporate climatic-based characteristics in bridge condition assessment to enable well-informed decision-making regarding the rehabilitation, repair, and renewal of these bridges.

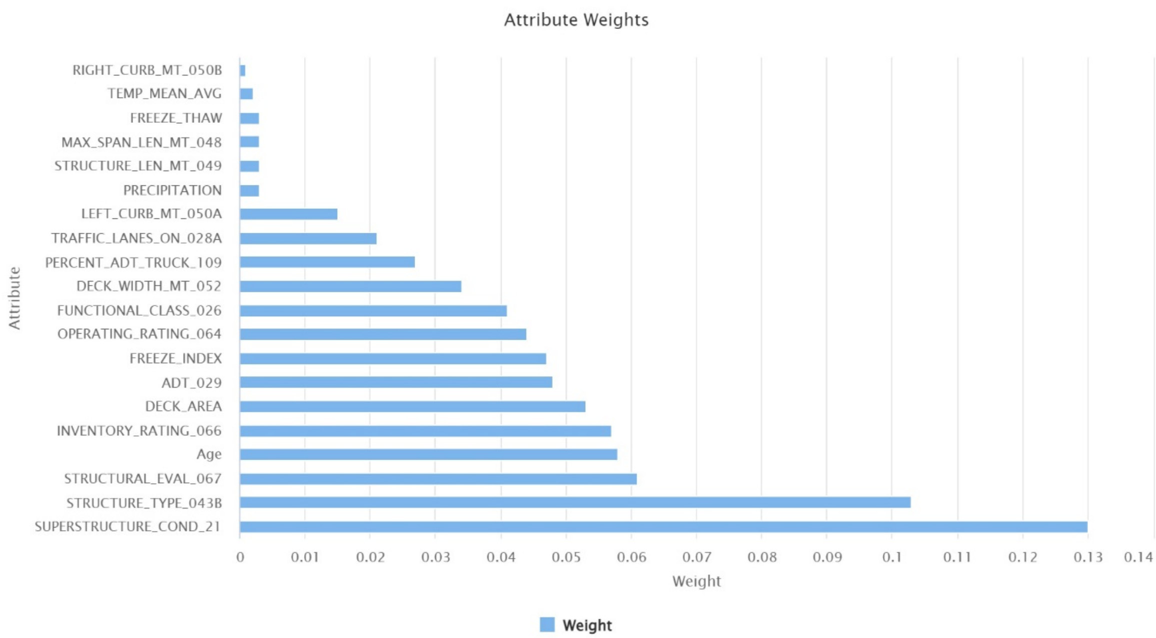

Figure 3. Attributes weights of importance

5. Conclusion

An investigation on the use of machine learning algorithms to forecast bridge conditions is presented in this publication. To carry out the condition assessment, the authors utilized open datasets from the Federal Highway Agency that included operational, structural, and climatic elements. Linear regression, decision trees, random forests, gradient boosted trees, naïve bases, and deep learning neural networks were the models whose performance was assessed. A chunk of the data was set aside solely for accuracy testing, whereas a portion was used to build and validate the prediction models. Cross-validation coupled with grid optimization were leveraged to automatically tune the hyperparameter and improve efficacy of prediction models. With a relative error of less than 4%, GBT was the best model to forecast the bridges' conditions. The freezing index was shown to be particularly important in forecasting the condition of concrete bridges among the climatic elements examined.

To address some of the limitations of this study, ongoing efforts are being made to construct timely-based deterioration curves and consider the dynamic nature of condition evaluation. Another extension would involve considering humidity and other climatic factors as they become available.

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