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Predictive Modeling of Bridge Conditions using Random Forest

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Abstract – The aging of transportation infrastructure, particularly bridges, poses significant challenges for monitoring and maintenance. This study explores the use of Random Forest algorithms for predictive modeling of bridge conditions, leveraging data from the US National Bridge Inventory (NBI). By focusing on data-driven insights, the research aims to enhance bridge management and improve maintenance strategies to enhance safety. Random Forest was selected for its robustness in handling complex, non-linear relationships and its effectiveness in assessing feature importance. The study involves comprehensive data collection and cleaning, followed by the identification of key variables that influence bridge condition ratings, such as age, construction materials, environmental factors, and maintenance history. Three distinct Random Forest models were built, one for each of the three bridge components: Deck, Substructure, and Superstructure, and the combined results were analyzed to obtain an overall view of the entire bridge. The dataset was divided into training and testing subsets to evaluate the model's performance. Results indicate a high accuracy of 84% in predicting bridge conditions, showcasing the model's ability to clarify the factors affecting bridge integrity. By identifying at-risk bridges, the model supports proactive maintenance strategies that can prevent costly repairs and reduce service disruptions. This research emphasizes the importance of data-driven decision-making, enabling more efficient resource allocation to prioritize maintenance where it is most needed. In summary, this study demonstrates the effectiveness of Random Forest in predictive modeling for bridge management, paving the way for more resilient and proactive approaches to ensure the longevity and reliability of bridge systems.

***Keywords*:** Bridge management, data analysis, predictive modeling, random forest.

1. Introduction

Transportation infrastructure, especially bridges, is vital for societal functioning. However, a significant portion of the U.S. bridge network is aging and requires ongoing maintenance to ensure safety. According to the U.S. Department of Transportation, many bridges are approaching the end of their designed lifespan, resulting in increased maintenance costs and safety risks. Traditional inspection methods rely heavily on human evaluation, which can be time-consuming, subjective, and costly. With advancements in data science and machine learning, there is a growing opportunity to automate the prediction of bridge conditions and optimize maintenance efforts. This study explores the application of Random Forest (RF) to predict bridge conditions. Utilizing data from the U.S. National Bridge Inventory (NBI), this research aims to enhance bridge management systems by developing a model that can forecast future bridge conditions and support data-driven maintenance prioritization. Predicting bridge conditions is crucial for optimizing maintenance schedules and ensuring transportation network safety. Insights from this study can help identify bridges at risk of deterioration, enabling transportation agencies to allocate resources more effectively and prevent costly repairs while minimizing disruptions.

2. Literature Review

Accurate prediction of bridge condition ratings is critical for effective maintenance and repair planning. Previous studies have extensively explored various machine learning algorithms for predicting bridge deck conditions. For instance, research has shown that Random Forest (RF), eXtreme Gradient Boosting (XGBoost), and Artificial Neural Networks (ANN) can effectively predict bridge deck conditions, with RF achieving an accuracy of 83.4% when utilizing historical data from the National Bridge Inventory (NBI) [1]. Another study emphasized the importance of feature selection, significantly reducing the number of variables, and highlighted the RF classifier as the most accurate method for predicting condition ratings [2].

Despite these advancements, much of the existing literature focuses exclusively on bridge decks, neglecting the condition assessments of substructures and superstructures. This gap is significant; comprehensive bridge management necessitates an understanding of all components to ensure safety and longevity. Moreover, while several studies have demonstrated the efficacy of machine learning algorithms, there remains a lack of national-level analyses that leverage extensive datasets encompassing various bridge types and conditions [3], [4]. This study addresses these gaps by employing Random Forest algorithms to model not only bridge decks but also substructures and superstructures, providing a holistic approach to bridge condition prediction. By utilizing a comprehensive dataset from the NBI and focusing on data-driven insights, we aim to enhance bridge management strategies, identify at-risk structures, and facilitate proactive maintenance [5]. This research demonstrates the potential of machine learning in optimizing resource allocation and improving safety across the entire bridge system, paving the way for more resilient infrastructure management practices.

3. Methodology

Our methodology involves data Collection and preprocessing, feature selection, and model training and evaluation to develop a robust predictive model for bridge conditions.

3.1. Data Collection and Preprocessing

The dataset utilized in this study is derived from the U.S. National Bridge Inventory (NBI), which contains over 600,000 bridge records from across the United States [8]. This dataset includes a variety of features, such as bridge age, type, material, location, traffic volume, environmental conditions, and maintenance history, alongside condition ratings for different bridge elements. The bridge elements have four defined condition states, defined by the AASHTO Manual based on the severity of deficiencies to the element: Condition State 1 – Good, Condition State 2 – Fair, Condition State 3 – Poor, and Condition State 4 – Severe [6], [7]. The condition rating of each bridge component (deck, substructure, and superstructure) was calculated as the weighted average of individual condition ratings of the component elements. The total points used in developing the model are 87,341, with the biggest proportion belonging to the substructure, followed by the deck, and the least portion belonging to the superstructure (refer to Fig. 1).

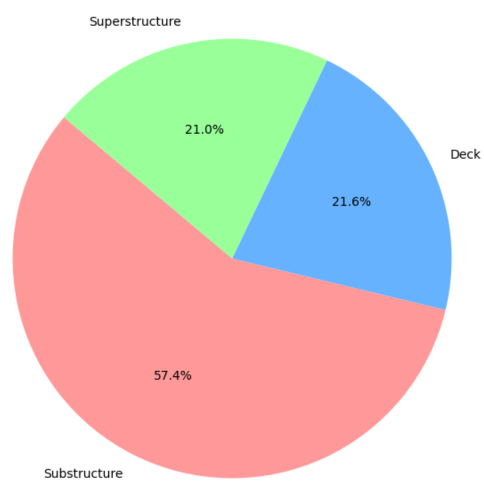

Fig. 1: Percentage of components in dataset.

The distribution of bridge condition ratings across the three bridge components reveals that Rating 1, indicating the best condition, is the most prevalent across all components, comprising the majority of the data. Rating 2 is less frequent but still notable, with the substructure showing the highest occurrence among the three components. In contrast, Ratings

3 and 4, representing poorer conditions, are minimal and scarcely represented in all components. Overall, the Substructure has the highest total frequency, suggesting it is the most represented component in the dataset, while the Deck and Superstructure display relatively similar total frequencies, following the same trend of condition distribution (refer to Fig. 2). The initial total number of features studied is 29; the frequency distributions of numerical features are illustrated by the histograms in Fig. 3.

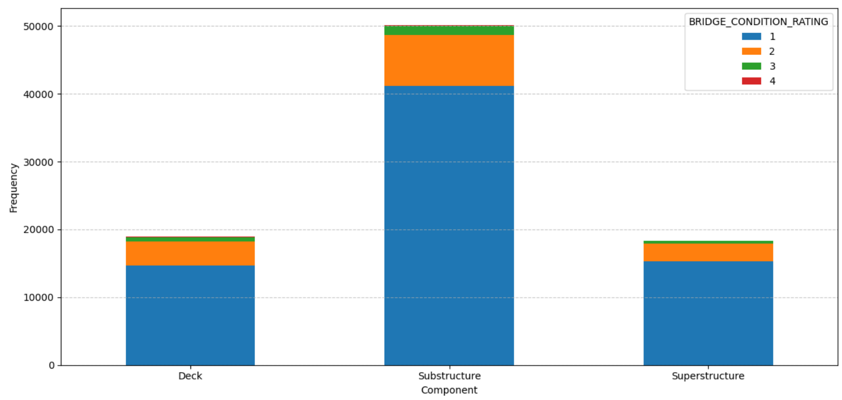

Fig. 2: Distribution of bridge condition ratings across components.

Fig. 3: Frequency distribution of numerical features.

To prepare the dataset for modeling, several preprocessing steps were undertaken. Missing values were addressed by imputing numerical columns with the median of that feature, while categorical columns were filled using the mode (the most frequent value). Categorical features, such as bridge type and material, were then converted into numerical values so that the machine learning model can accurately interpret the data.

3.2. Feature Selection

The model utilized Random Forest's capability to evaluate feature importance to identify key variables influencing bridge condition ratings. Significant features included bridge age, which indicates that older bridges are more likely to experience deterioration; bridge material, where different materials such as concrete, steel, and timber exhibit varying lifespans and maintenance needs; environmental factors, noting that bridges in regions with extreme weather conditions deteriorate faster; and maintenance history, highlighting that bridges with poor or infrequent maintenance are likely to degrade more quickly. The top 10 features were selected, and a correlation matrix was created to provide insights into the relationships between the selected features, helping to identify interdependencies and potential redundancies for more effective modelling. As shown in Fig.4, most features exhibit weak to negligible correlations, suggesting minimal interdependence and indicating that the features are largely independent, which reduces the risk of multicollinearity affecting the predictive model.

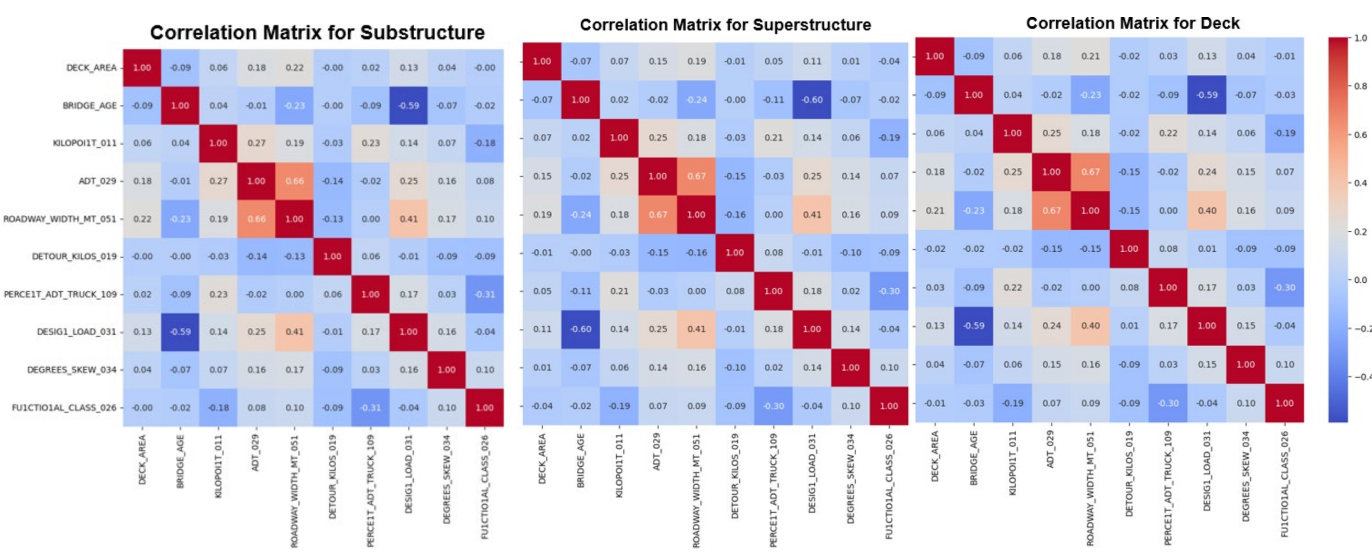

Fig. 4: Correlation matrix of selected features for each component.

3.3. Model Training and Evaluation

The dataset was divided into three distinct models for the Deck, Superstructure, and Substructure components of bridges. This segmentation was essential to address the unique characteristics and degradation patterns of each bridge component. These components are subjected to different loads, environmental conditions, and aging mechanisms. By treating them separately, the analysis can focus on the unique variables relevant to each component, leading to more accurate predictions and tailored maintenance strategies. Furthermore, this approach ensures that the models account for the specific engineering and functional requirements of each component, ultimately enhancing the reliability and interpretability of the results.

The dataset for each component was further split into training and testing subsets, with 80% used for training and 20% reserved for testing. The training phase utilized the Random Forest algorithm, optimized through a randomized search procedure that employed cross-validation to systematically identify the best hyperparameters. This process involved fitting three folds for each of the 20 candidate hyperparameter combinations, totaling 60 iterations. Cross-validation was crucial for ensuring that the models were robust and capable of generalizing well to unseen data, thus minimizing the risk of overfitting.

The optimized hyperparameters varied for each component model, reflecting the distinct data distributions and predictive predictive requirements of the Deck, Superstructure, and Substructure datasets. For the Deck model, the optimal parameters parameters included a larger number of trees and deeper decision paths, enabling the model to handle more complex relationships in the data. The Superstructure model similarly benefited from a greater tree depth but required slightly different splitting criteria to optimize its predictions. The Substructure model required fewer trees and a shallower depth, indicating that the underlying relationships in its data were less complex but still critical to model effectively.

Performance evaluation was conducted using metrics such as mean absolute percent error (MAPE), accuracy, precision, recall, F1 scores and confusion matrices. This comprehensive methodology ensured that each model captured the unique aspects of its corresponding bridge component, while the combined analysis provided an overarching view of bridge health, supporting data-driven maintenance and resource allocation decisions.

4. Results and Discussion

Looking at the feature importance analysis across bridge components, several key patterns emerge (refer to Fig. 5). The deck area consistently shows the highest importance across all three structural components (deck, superstructure, and substructure). Bridge age follows as the second most important feature, with particularly high importance for the substructure compared to the deck and superstructure. Traffic-related features like ADT (Average Daily Traffic) and kilometer-point measurements show moderate importance across all components. In contrast, features such as functional class and design load generally demonstrate lower importance values across all components, though design load shows slightly higher importance for the substructure. The relative consistency of feature rankings across components suggests that similar characteristics influence the condition of different bridge elements, though their degree of importance varies by component.

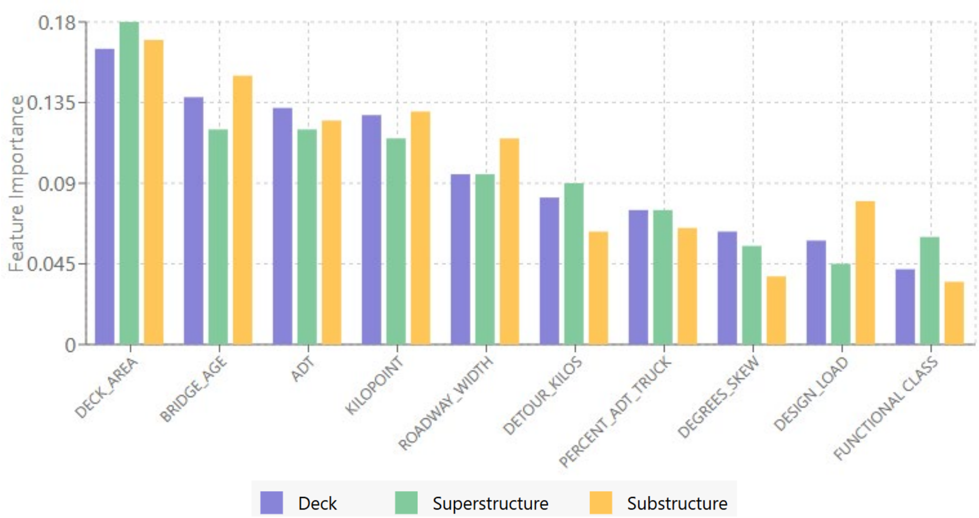

Fig. 5: Feature importance for bridge components.

The performance metrics for each bridge component and the combined model are summarized in Table 1 below. The combined bridge component models demonstrate a robust and comprehensive approach to bridge condition assessment, achieving a reasonable average accuracy of 84% and an average F1 score of 81%. With a relatively low mean absolute percentage error of 9%, the models exhibit consistent and reliable predictive capabilities across different structural elements. Although individual component models showed slight variations in performance, the overall methodology effectively captures the nuanced complexities of bridge structural health. The reasonable precision of 81% further underscores the models' ability to provide statistically significant and trustworthy insights into bridge condition evaluation.

Table 1: Summary of performance metrics.

Component	MAPE	Accuracy	Precision	Recall	F1 Score
Deck	11%	81%	79%	81%	78%
Superstructure	6%	88%	86%	88%	86%
Substructure	9%	83%	77%	83%	77%
Combined Model	9%	84%	81%	84%	81%

The confusion matrix visualizations provide a comprehensive overview of the predictive performance of the models for the different bridge components: superstructure, substructure, and deck (refer to Fig. 6). The matrices highlight the strong predictive performance of the bridge component models, particularly for the superstructure and substructure assessments. The superstructure model demonstrates a reasonable ability to accurately classify the majority of Actual 1 instances, showcasing its robust predictive capabilities. Similarly, the substructure model exhibits a balanced approach, maintaining a consistent level of accuracy across the different conditions.

While the models display these strengths, there are some areas for improvement, especially regarding the minority classes. Across the board, the models struggle to correctly identify Actual 3 and Actual 4 instances, often misclassifying them as Actual 1 or Actual 2. This suggests that further investigation into addressing class imbalance and enhancing the models' ability to accurately predict less common conditions could lead to even more comprehensive and reliable bridge condition assessments. Overall, the models' demonstrated strengths in predicting the dominant bridge component conditions provide a solid foundation for infrastructure monitoring and maintenance planning, showcasing the potential of this predictive modeling approach.

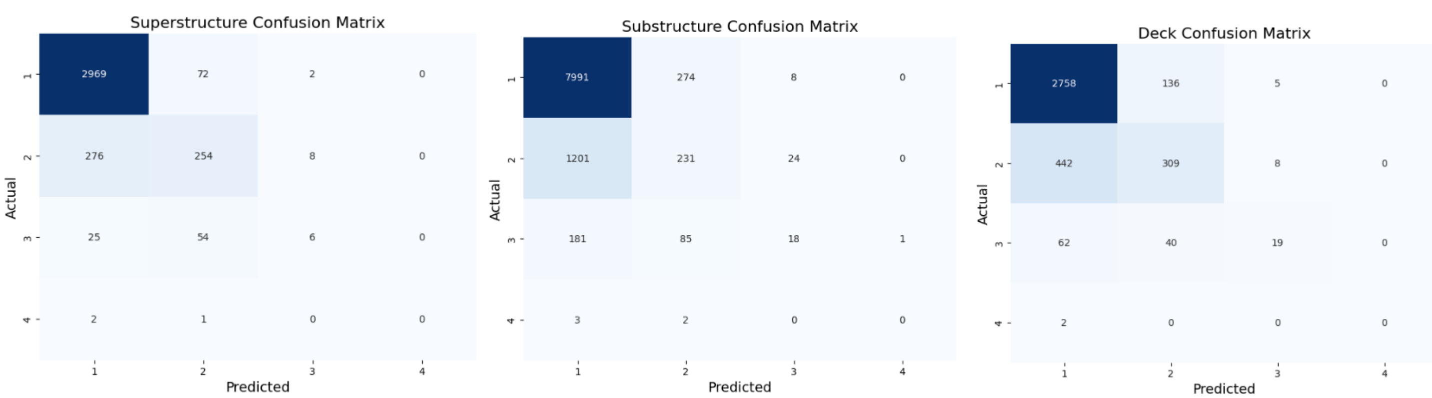

Fig. 6: Confusion matrix visualizations for bridge components.

5. Conclusion

This study demonstrates the effectiveness of Random Forest algorithms in predicting bridge conditions using the National Bridge Inventory dataset. The model provides valuable insights into the factors influencing bridge deterioration, which can help prioritize maintenance efforts. The combined model achieves a strong performance with an accuracy of 84%, and the findings suggest that Random Forest is a robust tool for bridge condition prediction. By providing early predictions of bridge deterioration, this model can assist bridge management systems in making data-driven decisions for maintenance prioritization. This can lead to cost savings and improved safety by reducing the risk of bridge failures.

To further enhance the models' performance, the observed class imbalance issues should be addressed, especially for the minority class 4 condition. This can be done by considering different strategies such as oversampling the minority class, undersampling the majority class, utilizing ensemble methods, applying class weighting, and conducting targeted feature engineering. As transportation networks continue to age, predictive modeling like this will play an increasingly important role in ensuring the long-term reliability and safety of infrastructure.

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