Fall 2021

Predicting Pavement Structural Condition Using Machine Learning Methods

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PREDICTING PAVEMENT STRUCTURAL CONDITION USING MACHINE LEARNING METHODS

by

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Bachelor of Science
Bangladesh University of Engineering and Technology, 2017

Submitted in Partial Fulfillment of the Requirements

For the Degree of Master of Science in

Civil Engineering

College of Engineering and Computing

University of South Carolina

2021

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DEDICATION

I dedicate this work to my beloved parents, Feroze Ahmed and Nasim Ahmed. I thank them for believing in me, motivating me, supporting through difficult times, and continuous care.

ACKNOWLEDGEMENTS

I would like to express my sincere gratitude to my advisor, Dr. Nathan Huynh, for his thoughtful guidance, patience, and support in completing the thesis.

I am very thankful for the support, encouragement, and critiques of my thesis committee members, Dr. Robert Mullen, Dr. Charles Pierce, and Dr. Yuche Chen. I would also like to express my appreciation to my lab mates and colleagues in my graduate school for all the help and to make my journey more colorful and

Finally, I would like to thank the South Carolina Department of Transportation (SCDOT) for supporting my graduate study at the University of South Carolina.

ABSTRACT

State departments of transportation recognize the need to incorporate pavement structural condition in their pavement performance models and/or decision processes used to select candidate projects for preservation, rehabilitation, or reconstruction at the network level. However, pavement structural condition data are costly to obtain. To this end, this paper develops and evaluates the effectiveness of two machine learning methods, Random Forest (RF) and eXtreme Gradient Boosting (XGBoost), for predicting a flexible pavement's structural condition. The aim is to be able to predict whether a pavement section's structural condition is poor or not based on Annual Average Daily Traffic (AADT), truck percentage, speed limit, pavement age, and soil regions. The structural condition of a pavement is considered poor if the Surface Curvature Index (SCI_{12}) is above 3.3. The models are developed using 950 miles of Traffic Speed Deflectometer (TSD) data collected along 8 primary routes in South Carolina. The performance of the machine learning models was compared with that of a logistic regression model. When the trained models are applied to the test data, the prediction results indicated that the RF and XGBoost models outperform the logistic regression model by 16% and 14%, respectively. RF outperformed XGBoost by 2%. With RF found to be the best among the three models evaluated, its performance was examined using other poor structural condition threshold values; its prediction accuracy is found to be robust across the different scenarios. Truck percentages, AADT, and pavement age are found to be significant factors on a pavement's structural condition.

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CHAPTER 1: INTRODUCTION

1.1 Background and Problem Statement

Currently, most state departments of transportation (DOTs) rely only on the pavement functional condition data to select candidate projects for preservation, rehabilitation, or reconstruction at the network level (Shrestha et al., 2018a). A pavement's functional condition is related to roughness and surface distresses, whereas a pavement's structural condition is related to its strength or carrying capacity. The functional performance considers safety in terms of skid resistance and smoothness. Surface condition data can provide information on structural conditions based on distress types (i.e., fatigue cracking gives an indication of structural failure). As part of this thesis, a survey of state DOTs was conducted which had 25 responses. The responses indicated that only 13% of the respondents currently use structural condition data to make decisions at the network level and 47.8% of the respondents plan to use structural condition data in the future. Previous studies have found that there is little correlation between a pavement's functional condition and a pavement structural condition (Flora, 2009; Bryce et al., 2013). Using South Carolina DOT's Traffic Speed Deflectometer (TSD) data, this thesis arrived at the same conclusion. This thesis calculated the Pearson correlation between the pavement structural and functional condition. It was found that 50% has low Pearson correlation (below ± 0.29), 27.5% has moderate correlation (between ± 0.30 and ± 0.49), and 22.5% has high correlation (between ± 0.5 and ± 1.0). This finding confirmed prior knowledge that a pavement's functional condition does not accurately portray its underlying condition

related to remaining service life or the potential for future deterioration. For this reason, several researchers have recommended the consideration of both pavement functional and structural condition for pavement management (Zaghloul et al., 1998; Ferne et al., 2013, Steele et al., 2015; Katicha et al., 2016).

To obtain pavement structural condition data, one approach involves the use of Falling Weight Deflectometer (FWD). This device has been widely used since 1980 for structural evaluation of both flexible and concrete pavements (Chai et al., 2016). This method measures the pavement deflection with high accuracy (Zihan et al., 2019). But this device has the following limitations: 1) FWD operates at slow speed and measures pavement deflection at discrete points along the pavement sections and thus does not provide the complete profile of the roadway, and 2) this device requires lane closures which disrupts traffic operations. These limitations make FWD unsuitable to be used at the network level for pavement management (Shrestha et al., 2018a; Nasimifar et al., 2019). In contrast, TSD measures pavement deflections continuously at traffic speed rather than at discrete points and does not require lane closures like FWD (Manoharan et al., 2018; Chai et al., 2016). Several state DOTs have begun to explore the use of TSD data, including South Carolina DOT (SCDOT) from which this study is based.

The use of TSD in the U.S. is fairly new. Some of the recent TSD related studies related to pavement structural condition indicator parameters are mentioned below. Several studies have proposed indicators and threshold values to quantify a pavement's structural condition as good, fair, or poor. Shrestha et al. (2018a) proposed the use of Surface Curvature Index (SCI300) to predict a pavement's structural condition and developed threshold values for this indicator. Manoharan et al. (2018) proposed the use of Adjusted

Structural Number; Shrestha et al. (2018b) proposed the use of Deflection Slope Index (DSI); and Manoharan et al. (2020) proposed the use of Remaining Structural Life. Several studies used TSD data to predict the pavement structural conditions. Shrestha et al. (2018b) developed a pavement deterioration model based on pavement age and DSI, and Zihan et al. (2018) developed a non-linear model to predict a pavement's Structural Number (SN). To date, no study has investigated the use of machine learning models to predict a pavement's structural condition. Since machine learning models are not constrained by a specific model structure and can handle large data sets with any degree of complexity (Zhang & Haghani, 2015), they may be more suitable than traditional parametric methods.

1.2 Scope of the Study

The objective of this thesis is to develop two machine learning models, Random Forest (RF) and eXtreme Gradient Boosting (XGBoost), to predict a pavement's structural condition using influencing factors with readily available data: Annual Average Daily Traffic (AADT), truck percentage, speed limit, pavement age, and soil regions. This thesis assumed that there exists a correlation between the pavement structural condition and the variables. In some scenarios, this may not exist as strongly as in the dataset used in the study. The goal is to evaluate the effectiveness of the machine learning techniques to predict pavement structural condition. Such type of model will assist state highway agencies, counties, and municipalities in incorporating structural condition into pavement performance models or decision processes used to select candidate projects at the network level. The models' performances are compared with each other and that of a traditional parametric approach, logistic regression, using TSD data from South Carolina.

1.3 Organization of Thesis

The thesis is divided into six (6) chapters. Chapter 1 provides the research background and problem statement. Chapter 2 provides a summary of TSD related studies. This chapter also includes pavement studies that applied machine learning models to predict the pavement conditions. Chapter 3 discusses the source of the TSD data, and the procedure taken to prepare the data for modeling. Chapter 4 presents the mathematical details of RF and XGBoost, as well as that of the logistic regression. Chapter 5 presents and discusses the prediction results of the three models. Lastly, Chapter 6 provides a summary of the study and concluding remarks.

CHAPTER 2: LITERATURE REVIEW

The literature review is divided into two sections. The first section describes the TSD related studies, and the second section describes the machine learning applications in pavement condition prediction.

2.1 TSD Related Studies

The studies which are based on the pavement data collected by the Traffic Speed Deflectometer (TSD) device are described in the following sub-sections.

2.1.1 Pavement Structural Condition Predictor Parameters

Several different indicators have been proposed to quantify pavement structural condition. Shrestha et al. (2018a) proposed the use of SCI_{300}. SCI_{300} (or SCI_{12} in English Customary). Subsequently, Shrestha et. al. (2018b) proposed the use of Deflection Slope Index (DSI) and developed a pavement deterioration model based on pavement age and DSI. Virginia DOT (VDOT) currently uses effective SN, calculated using Equation 1 (Katicha et al., 2020).

$$SN_{eff} = k_1 SIP^{k2} H_P^{k3} \tag{1}$$

where,

SN_{eff} = effective Structural Number

H_P = total pavement thickness (mm)

SIP = structural index of pavement, calculated as $D_0 - D_{1.5H_P}$

Rohde (1994) estimated coefficients k_1, k_2, and k_3 for an asphalt pavement to be 0.4728, -0.4810, and 0.7581, respectively. Nasimifar et al. (2019) recommended that these coefficients be adjusted to 0.4369, -0.4768, and 0.8182 if the deflection measurements are obtained using a TSD.

Manoharan et. al. (2020) proposed the use of Remaining Structural Life (RSL) and developed a method to derive RSL from D_0. This paper developed methodology for calculating the pavement Remaining Structural Life (RSL) from Maximum Deflection (D_0) and provided a detailed step by step procedure. This parameter would assist the asset manager for better rehabilitation decisions at the network level. This study classified the pavements into five categories based on the remaining structural life. Table 2.1 shows the classification of pavement based on remaining structural life.

Table 2.1 Pavement Categories based on Remaining Structural Life

Bands	Remaining life is >= years	Remaining life is < years
Very Good	30	
Good	20	29
Fair	10	19
Poor	4	9
Very Poor	0	3

2.1.2 Development of Threshold Values

Several studies have developed threshold values to quantify the pavement structural condition as good, fair or poor. Shrestha et al. (2018b) developed thresholds for Deflection

Slope Index (DSI). Pavement sections with DSI values below 5.90 are considered good, between 5.90 and 15.90 are considered fair, and above 15.90 are considered poor. Shrestha et. al. (2018a) also developed threshold values for SCI_{300}. For primary routes, their suggested threshold value for good pavement is less than 4.9, fair is between 4.9 and 6.2, and poor is greater than 6.2. Manoharan et al. (2018) developed threshold values for adjusted Structural Number (SNP) and D_0 as shown Table 2.2. The relationship between SNP and D_0 (obtained using TSD data) is shown in equations 2 and 3. SNP in equations 2 and 3 are determined using FWD data.

$$SNP = 82.3 \times TSD_{D_0}{}^{-0.47} \tag{2}$$

$$SNP = 3.2 \times TSD_{D_0}{}^{-0.52} \tag{3}$$

Table 2.2 Pavement Structural Conditions based on SNP and D_0

Category	Adjusted Structural Number (SNP)		TSD Maximum Deflection (D_0)	
	Lower limit	Upper limit	Lower limit	Upper limit
Very good	≥ 8		≤ 160	
Good	≥ 6	<8	≤ 300	>160
Fair	≥ 4	<6	≤ 650	>300
Poor	≥ 2.5	<4	≤ 1535	>650

2.1.3 Network Level Pavement Management

Shrestha et al. (2018a) investigated the use of pavement structural condition data for system-wide pavement management, where a framework to assist Virginia Department of Transportation (VDOT) to utilize SCI_{300} in their Pavement Management System (PMS) was developed. VDOT uses levels of pavement distresses to select pavement maintenance categories and Critical Condition Index (CCI) as an additional filter; CCI is equivalent to

the SCDOT's PQI and it ranges from 0 to 100 where a 0 indicates very poor pavement and a 100 indicates an excellent pavement. Shrestha et al. (2018a) recommended the use of SCI_{300} at the second stage to make the final rehabilitation decision. Table 2.3 illustrates the treatment categories used by VDOT.

Table 2.3 Treatment Categories Used by VDOT

Treatment Categories	Expression Code
Do Nothing (DN)	1
Preventive Maintenance (PM)	2
Corrective Maintenance (CM)	3
Rehabilitation Maintenance (RM)	4
Reconstruction (RC)	5

Nasimifar et al. (2019) proposed a method to compute and utilize Structural Number (SN) from the TSD collected data for network level pavement management system application. UK Highway agency implemented Falling Weight Deflectometer (FWD) or Deflectometer to collect pavement deflection data since 2000. But the procedure had some limitations: (a). slow moving or static measurement techniques which are expensive to operate (b). hazardous for operators, and (c). disruptive for road users. Due to these limitations, the use of FWD or. Deflectometer was discontinued in 2000 for routine level assessment and only limited for project-level. Transport Research Laboratory (TRL) developed a methodology for assessing the structural condition of the network on regular surveys carried out at traffic speed under the funding of UK Highway agency. They developed an algorithm to convert each of the 1m TSD slopes to an estimated peak Deflectometer value. The procedure combined the estimated peak Deflectometer with construction and traffic information to measure structural condition for each 100 m length

pavement section. These measures were used to assign one of the categories mentioned in Table 2.4 to each 100 m length (Ferne et al. 2013).

Table 2.4 UK Network Structural Condition Categories

Category	Description
1	Flexible pavements without any need for structural maintenance
2	Flexible pavements unlikely to need structural maintenance
3	Flexible pavements likely to need structural maintenance
4	Flexible pavements very likely to need structural maintenance

2.1.4 Comparison between FWD and TSD

Several studies have compared the measurements obtained from TSD against FWD. Chai et al. (2016), Manoharan et al. (2018) and Muller and Roberts (2013) showed that TSD and FWD maximum deflections (D_0) are highly correlated. The goodness of fit of their linear regression models (R^2) are 0.88, 0.883 and 0.888, respectively. Muller and Roberts (2013) also showed that TSD and FWD SCI_{300} are highly correlated with R^2 = 0.853. All three of these studies used data collected from Queensland, Australia. Zihan et al. (2018) used TSD and FWD data from Louisiana and Idaho to compare the Structural Number (SN) calculated using these measurements. They found that the SN calculated using TSD data to be highly correlated with the SN calculated using FWD data; their linear regression model's R^2 value was 0.931 for the training dataset and 0.887 for the test dataset. Instead of using linear regression as those mentioned above, Levenberg et al. (2019) proposed the use of a Taylor diagram to visualize the similarity between TSD and FWD.

2.1.5 Other TSD Related Studies

Anticipating the use of TSD data in future practices, several studies have begun to

explore how to make use of such data. Maser et al. (2017) developed a geodatabase using ArcGIS to incorporate pavement condition data to assist DOT personnel to visualize pavement condition and select a suitable rehabilitation strategy. Nasimifar et al. (2017) proposed two approaches to back-calculate flexible pavement layer moduli from TSD data. Similarly, Elbagalati et al. (2017) and Nielson (2019) developed methodologies to incorporate TSD measurements in the back-calculation analysis. Elbagalati et al. (2017) found that the back-calculated moduli obtained from TSD and FWD deflection measurements had good agreement. Zofka et al. (2015) examined external factors that may have a significant effect on the TSD measurements. They proposed a probabilistic model to account for wind and pavement roughness. Nasimifar et al. (2018) developed a method to adjust SCI to a reference temperature. The authors stated that the temperature adjustment is essential to correctly assess the pavement structural evaluation since the asphalt layer is sensitive to temperature. Nasimifar et al. (2015) and Nasimifar et al. (2016) have investigated the use of 3D-Move Analysis Software to simulate TSD measurements.

2.2 Machine Learning Applications in Pavement Condition Prediction

Machine learning, a form of Artificial Intelligence (AI), has been applied widely in transportation applications. Its popularity is due to its ability to learn the latent patterns of historical data to model the behavior of a system. This literature focuses on the research papers that developed various machine learning methods to predict the pavement conditions.

2.2.1 Artificial Neural Network (ANN) in Pavement Condition Prediction

Schwartz (1993) developed Artificial Neural Network (ANN) to predict the distress

density. This paper used pavement age, traffic, and subgrade strength as the input variables. George and Shekharan (1998) predicted Pavement Condition Rating (PCR) using Artificial Neural Network (ANN) from different distress types. Van der Gryp et al. (1998) applied Feed-forward Artificial Neural Network to predict the Visual Condition Index using various distress types and severities as the input variables. Kargah-Ostadi et al. (2010) employed Artificial Neural Network pattern recognition to predict the International Roughness Index (IRI). This research used initial roughness, pavement age, traffic volume, climatic condition, structural property, subgrade properties, drainage type and conditions, maintenance, and rehabilitation treatment as the variables. From the literature, it has been found that ANN has been applied only to predict the pavement functional condition not for structural condition.

2.2.2 Backpropagation Neural Network (BPNN) in Pavement Condition Prediction

Attoh-Okine (1994) predicted roughness progression using Backpropagation Neural Network. Structural deformation, incremental traffic loadings, cracking and thickness of surface layer, rut depth, surface defects, environmental variables, road age were used by this paper to develop the model. Eldin and Senouci (1995) proposed Backpropagation Neural Network to predict the Pavement Condition Index (PCI) using various distress types. Lin et al. (2003) considered Backpropagation Neural Network to predict the International Roughness Index (IRI) by using various distress types. Backpropagation Neural Network was employed by Choi et al. (2004) to predict the International Roughness Index (IRI). This paper used stiffness, asphalt layer thickness, temperature, material types, air void, viscosity, traffic load, pavement age as the variables. Yang (2004) predicted Pavement Condition Rating (PCR) from the variables crack index

time series, pavement type, pavement age, pavement cycle by using Backpropagation Neural Network method. It can be concluded that Backpropagation Neural Network has not been applied for pavement structural condition prediction.

2.2.3 Other Machine Learning Applications in Pavement Condition Prediction

Kargah-Ostadi and Stoffels (2015) applied various machine learning techniques (Artificial Neural Networks, Support Vector Machines, Radial Basis Function Network) to predict International Roughness Index (IRI). Mazari and Rodriguez (2016) evaluated the performance of Artificial Neural Networks, Gene Expression Programming to predict the International Roughness Index (IRI). To predict the International Roughness Index (IRI), Ziari et al. (2016a) developed Support Vector Machine, Ziari et al. (2016b) used Artificial neural networks, group method of data handling, and Ziari et al. (2016c) applied Group method of data handling, Adaptive neuro fuzzy inference system. Barua et al. (2020) developed gradient boosting algorithm to predict the Pavement Condition Index (PCI). It can be concluded that no machine learning methods have been used to predict the pavement structural condition. Table 2.5 provides a list of studies that have applied machine learning models to predict pavement conditions.

Table 2.5 Summary of ML Applications in Pavement Condition Prediction

Author	Method	Pavement Condition Indicator
Schwartz (1993)	ANN	Distress Density
George and Shekharan (1998)	ANN	PCR
Van der Gryp et al. (1998)	Feed-forward Artificial Neural Network	Visual Condition Index
Kargah-Ostadi et al. (2010)	ANN	IRI
Attoh-Okine (1994)	BPNN	Roughness Progression
Eldin and Senouci (1995)	BPNN	PCI
Lin et al. (2003)	BPNN	IRI
Choi et al. (2004)	BPNN	IRI
Yang (2004)	BPNN	PCR
Kargah-Ostadi and Stoffels (2015)	ANN, SVM, Radial Basis Function Network	IRI
Mazari and Rodriguez (2016)	ANN, Gene Expression Programming	IRI
Ziari et al. (2016a)	SVM	IRI
Ziari et al. (2016b)	ANN	IRI
Ziari et al. (2016c)	SVM	IRI
Barua et al. (2020)	GBM	PCI
Marcelino et al. (2019)	RF	IRI
Mousa et al. (2019)	XGBoost	PSL

2.2.4 Random Forest (RF) and eXtreme Gradient Boosting (XGBoost)

Two promising models for predicting pavement structural condition are random forest and eXtreme Gradient Boosting. They are motivated by the work of Marcelino et al. (2019) and Mousa et al. (2019). Marcelino et al. (2019) explained the limitations of the Artificial Neural Network (ANN) based on the literature review, which are widely used for pavement condition prediction. The main problem of ANN is the overfitting problem. Overfitting occurs when the model error on the training data is small but on the test data is large, which negatively affects the performance of the model on the new data. On the other

hand, the main advantage of Random Forest (RF) is that RF reduces overfitting in decision trees and helps to increase the accuracy. This paper proposed the use of Random Forest in pavement performance prediction. Mousa et al. (2019) developed XGBoost model for prediction of Pavement Service Life (PSL) and proposed this type of model's use in pavement applications as the literature lacks the use of XGBoost model in pavement performance prediction. This paper also mentioned that tree-based algorithm is becoming popular in solving classification and regression problems and the literature lacks the use of XGBoost model in pavement performance prediction. XGBoost is an advanced implementation of the gradient boosting method. This method controls the noise in data and thus prevents the overfitting. This technique outperforms the other tree-based algorithms in terms of prediction accuracy. The additional advantages of the XGBoost model are its efficiency, feasibility, accuracy, and short processing time.

2.3 Research Needs

From the first section of the literature review, it can be concluded that no research developed any machine learning model to predict the pavement structural condition using the TSD collected data. From the second section, it can be concluded that all of the previous studies that applied machine learning models focused on pavement functional condition. No research was found to predict the pavement structural condition, which is crucial for making decisions regarding pavement rehabilitation, preservation, or reconstruction. This can be considered as a potential research gap, which is addressed by this thesis. It would be beneficial if the pavement deflection data can be collected using the TSD periodically. However, this is cost prohibitive. The machine learning models developed in this thesis

will aim to reduce the frequency at which TSD data need to be collected, and thereby, reduce time, effort, and costs for state DOTs.

CHAPTER 3: DATA DESCRIPTION

3.1 Sources of TSD Data

TSD is a continuous pavement deflection-measuring device that measures pavement response to an applied load. It was developed by Greenwood Engineering in the early 2000's using doppler laser-based technology. TSDs are being used by many transportation agencies around the world. As part of the pooled fund studies (i.e., TPF-5(282) and 5(385)), the SCDOT obtained TSD data for approximately 950 miles along 8 primary routes in the state of South Carolina. A map of the routes selected by SCDOT to obtain TSD data for is shown in Figure 3.1. The length of TSD measurements obtained for each route is summarized below, in descending order.

- SC-9: 231 miles
- US-321: 216 miles
- US-378: 201 miles
- US-178: 181 miles
- US-29: 37 miles
- US-78: 36 miles
- US-17: 19 miles
- US-501: 12 miles

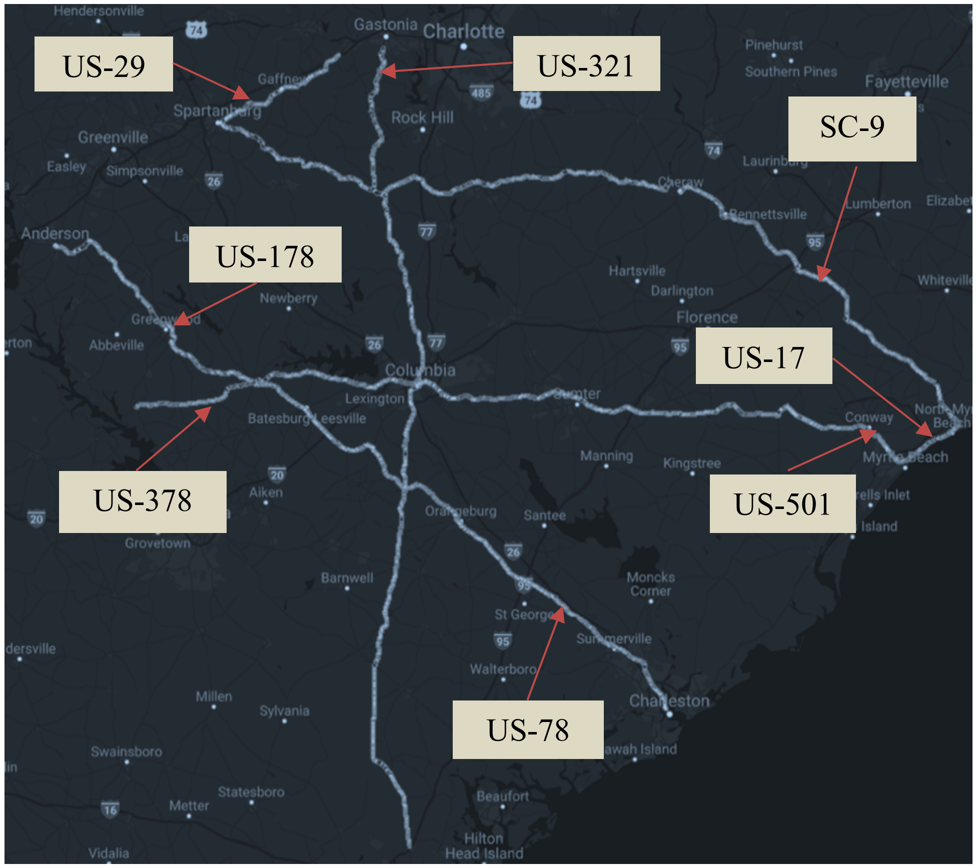

Figure 3.1 Primary routes selected by SCDOT to have TSD data collected

The TSD data were obtained by ARRB using their Intelligent Pavement Assessment Vehicle (IPAVe). IPAVe (shown in Figure 3.2) is a semi-trailer truck that is equipped with six Doppler sensors to measure pavement deflection located at 110 mm (~4 in.), 210 mm (~8 in.), 310 mm (~12 in.), 610 mm (~24 in.), 910 mm (~36 in.) and 1510 mm (~60 in.) from the center of the wheel load. The pavement structural condition index or surface curvature index (SCI) can be derived from the deflection slope. In this thesis, SCI_{12} is used to quantify pavement structural condition. It is the difference between D_0 and D_{12}, where D_0 is the maximum deflection (under the applied load) and D_{12} is the deflection at 12 in (or 300 mm) from the applied load.

Figure 3.2 iPAVe used to collect pavement conditions in South Carolina

3.2 Data Preparation

The TSD data were collected in 2019 at 0.01-mile increments by IPAVe which used the World Geodetic System (WGS84) coordinate system. TSD truck collected the data in one direction along the highway. The SCDOT's roadway and traffic data, such as annual average daily traffic (AADT), are available in the North American Datum (NAD83) coordinate system. To enable the modeling of TSD data with respect to SCDOT roadway and traffic data, ESRI's ArcMap 10.8.1 was used to convert TSD data from WGS84 to NAD83, and a Python program was developed to pair TSD data with roadway data by segments. The SCDOT defines segments as those with common pavement quality, AADT, and number of lanes.

SCI_{12} was used to quantify a pavement as structurally good, fair, or poor. Table 3.1 shows the SCI_{12} threshold values, which were developed based on assumptions. For example, if the pavement segments have SCI_{12} threshold values less than 1.6 are considered

good. Pavement segments with SCI_{12} values between 1.6 and 3.3 are considered fair, and SCI_{12} values above 3.3 are considered poor. To validate the threshold values that we assumed, prediction models were developed by increasing the poor threshold range from 10% to 50% at 10% interval. This is discussed in the Result and Discussion Chapter in details.

Table 3.1 SCI_{12} Thresholds Value

Pavement Condition	SCI_{12} Thresholds
Good	< 1.6
Fair	1.6 – 3.3
Poor	> 3.3

Based on the specified thresholds, there are 18.38% segments with good pavement, 30.12% with fair pavement, and 51.5% with poor pavement. Due to the need to have a balanced dataset when applying machine learning models, good and fair categories are combined and categorized as non-poor pavement. In the model, the response variable was a binary variable. If the pavement was structurally poor, it was identified as "1", otherwise "0".

The input variables in this study are: AADT (Annual Average Daily Traffic), truck percentages, speed limit, pavement age, and soil regions. All these variables are expected to have a significant effect on the pavement structural condition.

3.3 Description of Variables

Figure 3.3 shows the percentages of poor and non-poor pavement segments for each route. Collectively, there are 8 routes with TSD data and 800 pavement segments. Overall, 51.5% of pavement segments have poor structural condition, and 48.5% have non-poor

structural condition. Note that these percentages yield a balanced dataset necessary for training machine learning models. The three routes with shortest length are US-78, US-17, and US-501, and their lengths are 36, 19, and 12 miles, respectively. These three routes have a greater percentage of non-poor structural condition relative to the other routes. US-178 has equal percentages of poor and non-poor pavement segments. The three routes with longest length are SC-9, US-321, and US-378, and their lengths range from 200 to 231 miles. Among the three longest routes, SC-9 has a larger percentage of segments with non-poor structural condition.

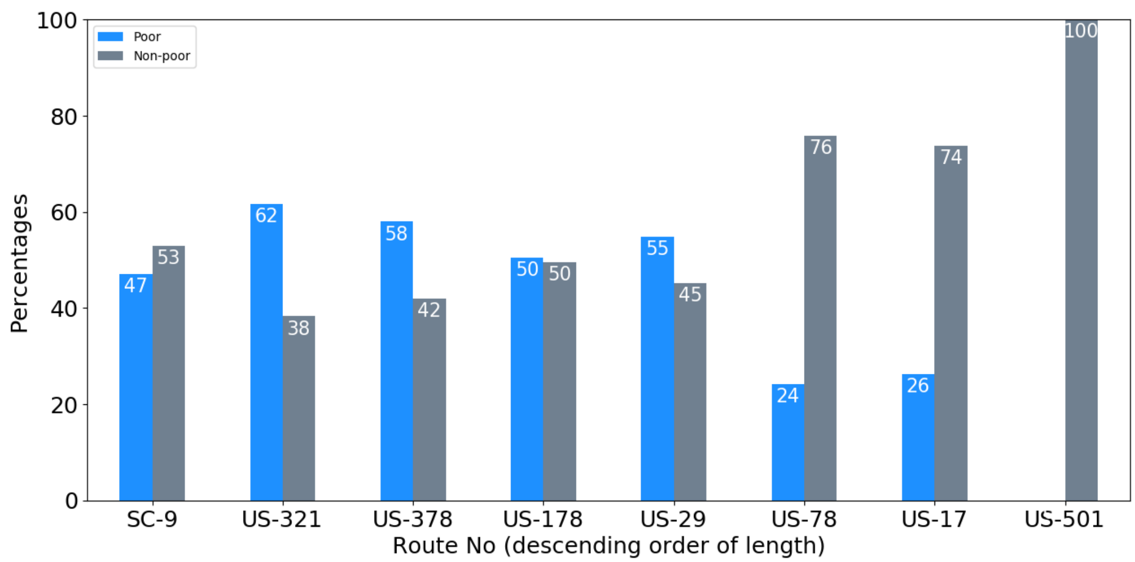

Figure 3.3 Percentages of segments with poor and non-poor structural conditions

Figures 3.4, 3.5, and 3.6 show boxplots of AADT, truck percentage, and speed limit for each route, respectively. The red line in the boxplot denotes the median value (50th percentile), the blue box denotes the inter-quantile range from 25th percentile to 75th percentile, and the two whiskers denote the 90% range, from 5th percentile to 95th percentile. It can be seen from the boxplots that the shortest two routes (US-17 and US-501) have significantly higher AADT than the other routes, and the three longest routes

have relatively higher truck percentages. As shown, the mean speed limit is either 45 mph (miles per hour) or 55 mph, but there is considerable variation in speed. Take US-178, for example, some segments on it have speed limits as low as 15 mph while others have speed limits of 55 mph.

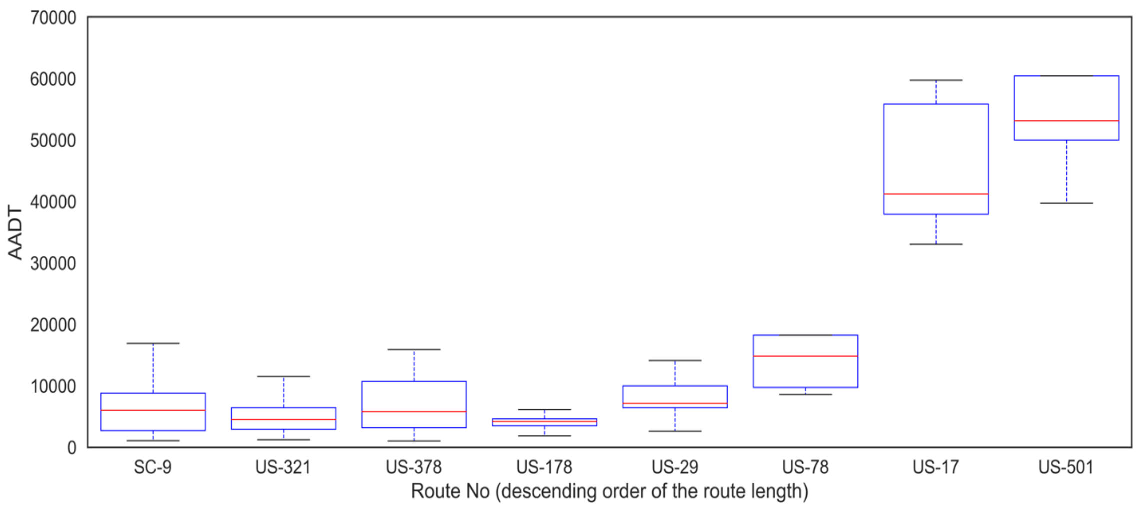

Figure 3.4 Boxplots of segments' AADTs for each route

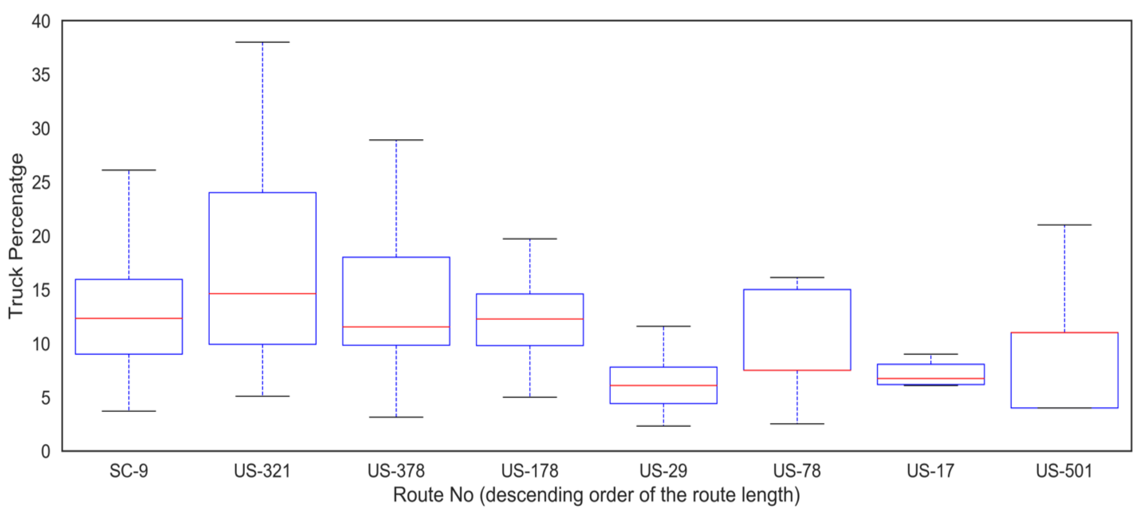

Figure 3.5 Boxplots of segments' truck percentages for each route

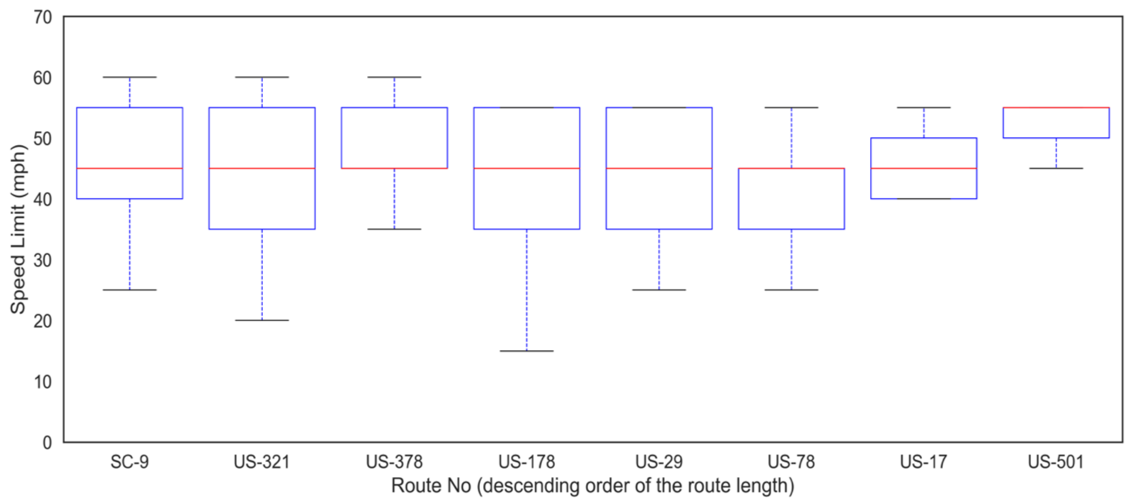

Figure 3.6 Boxplots of segments' speed limit for each route

Pavement age was calculated from the rehabilitation year data. The rehabilitation year of the segments was collected from the Highway Pavement Management System of South Carolina Department of Transportation (SCDOT). This thesis calculated pavement age by subtracting the rehabilitation year from 2019. As the TSD data was collected in 2019, this year was used for pavement age calculation. For example, if the rehabilitation of a segment was conducted in 2011, then the age of this segment is 8 years. The missing value of this variable was handled with the “Mice” Package in R. Figure 3.7 shows the boxplots of segments’ pavement age of each route.

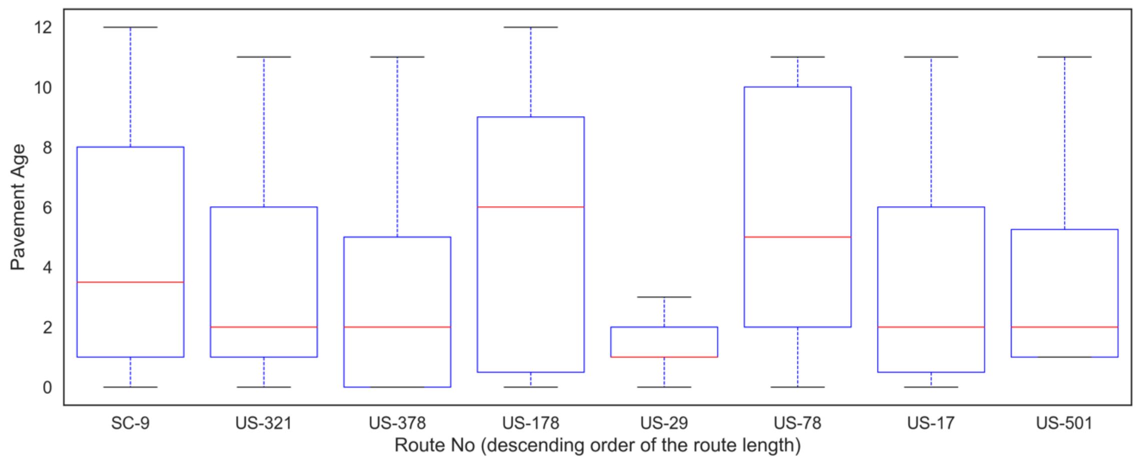

Figure 3.7 Boxplots of segments' pavement age for each route

The soil regions of the TSD routes were selected based on Sasanakul et al. (2019). According to this research, the soil map of South Carolina is divided into four regions: Piedmont, Upper Coastal Plain, Middle Coastal Plain, and Lower Coastal Plain. Each TSD route consists of several counties. First, it was checked in which region each county is located within the soil map. In few cases, if the county falls into the two regions of the soil map, the region where the maximum portion of the county falls was considered. This study used this variable as the dummy variable in the model. For example, a variable named "Piedmont Region" was created. If the county falls in this region, it was identified as 1, otherwise 0. Figure 3.8 shows the soil regions of South Carolina, which is taken from Sasanakul et al. (2019).

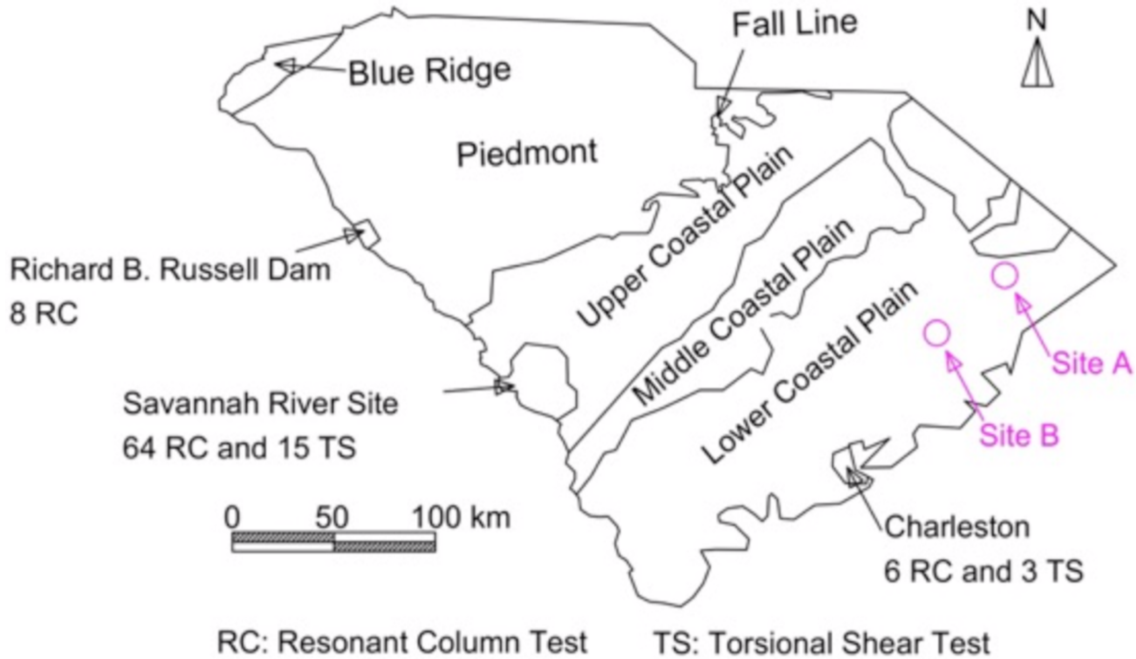

Figure 3.8 Soil regions of South Carolina

CHAPTER 4: METHODOLOGY

The following provides a brief overview of RF, XGBoost, and logistic regression. Readers are referred to the work of Jiang et al. (2016) for a comprehensive explanation of RF, Gong et al. (2019) for explanation of XGBoost, and Rezapour et al. (2020) for explanation of logistic regression. With each of these models, the goal is to predict a pavement's structural condition, specifically whether it is poor or non-poor; thus, the response variable has only two outcomes. The explanatory variables used to predict the outcome are AADT, truck percentage, speed limit, pavement age and soil regions of each segment. Figure 4.1 shows the steps for developing a machine learning model.

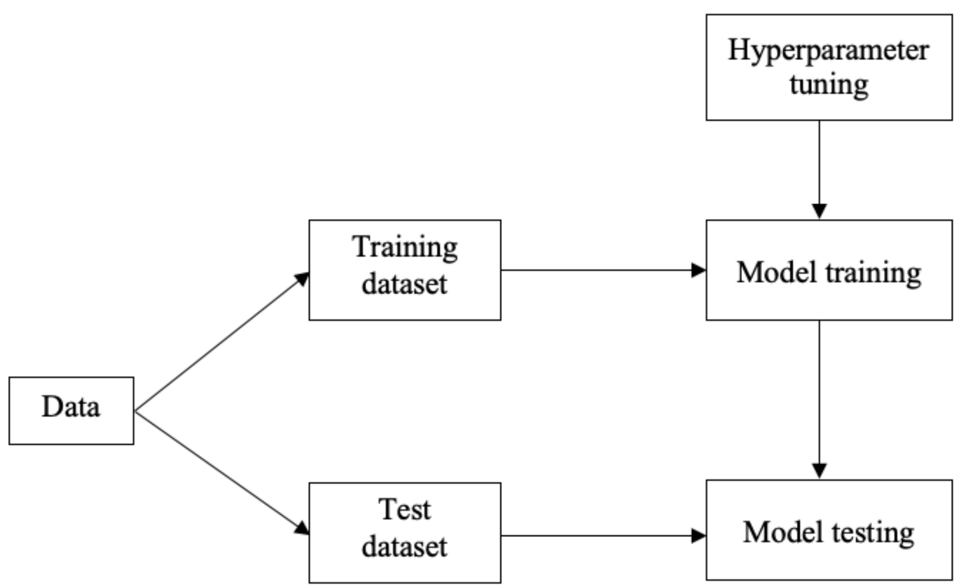

Figure 4.1 Steps for developing a machine learning model

4.1 Random Forest (RF)

RF is a supervised machine learning technique. This method is an ensemble meta-estimator that combines multiple decision trees on various sub-samples of the dataset (Uddin et al., 2021). It randomly selects different samples from the training dataset and determines the prediction accuracy of each sample. The samples are drawn with replacement and each tree in the ensemble is built using the drawn samples (Uddin et al., 2021). When splitting the node during construction of the tree, each node is split using the best among a subset of predictors randomly chosen at that node (Iranitalab & Khattak, 2017) and splitting is based on the Gini index (i.e., a measure of node purity) or entropy (i.e., a measure of node impurity) (Das et al., 2020). The prediction accuracy reported by RF is the average of the samples' prediction accuracies.

4.2 eXtreme Gradient Boosting (XGBoost)

eXtreme Gradient Boosting (XGBoost) is a supervised machine learning technique, which can be used for both classification and regression problems. This technique is an implementation of the Gradient Boosting algorithm which has been shown to provide better prediction accuracy than the gradient boosting method (Das et al., 2020). The gradient boosting approach utilizes gradient descent at each iteration to minimize the loss function. It also utilizes the second-order gradient of the loss function to obtain information regarding gradient direction and minimum loss function. The XGBoost model develops a prediction model by combining multiple weak learners. Each model learns from the previous model and builds a strong model by adjusting weights in a sequential manner. The XGBoost model can be expressed mathematically as (Kidando et al., 2021).

$$\hat{y}_i^{(t)} = \sum_{k=1}^{t} f_k(x_i) = \hat{y}_i^{(t-1)} + f_t(x_i) \quad (4)$$

Where $f_t(x_i)$ is the newly generated tree model, t is the total number of base tree models, and x_i are input data.

4.3 Logistic Regression

A logistic regression is a special case of multiple regression where the response variable (also known as dependent variable) has only two outcomes. Mathematically, it is expressed as:

$$\ln\left(\frac{P_n(i)}{1-P_n(i)}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \dots\dots\dots\dots + \beta_n x_n \quad (5)$$

$$\frac{P_n(i)}{1-P_n(i)} = \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots\dots + \beta_n x_n) \quad (6)$$

$$P_n(i) = \frac{\exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n)}{1 + \exp(\beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_n x_n)} \quad (7)$$

where,

$P_n(i)$ = probability of choosing a category

β_0 = intercept

x_n = predictor variables

β_n= coefficients of the corresponding variables

When applying logistic regression, the data should not have any outliers. Also, there should not be high correlations (multicollinearity) among the explanatory variables. This can be assessed by examining the correlation matrix among the predictors and ensuring correlation coefficients among explanatory variables are less than 0.90.

4.4 Machine Learning Models' Hyperparameters Tuning

The machine learning models were developed in R using the caret package. After splitting the dataset into training and testing, 70% and 30%, respectively, 10-fold cross-validation was conducted to train the RF and XGBoost models. The training data were used to train the model, and the testing data were used to evaluate the prediction accuracy of the models. For the RF model, a parameter named "randomly selected predictors" was tuned. This parameter indicates the number of variables randomly sampled at each split during the construction of a tree. It was found that when this parameter is set to 4, it provided the best RF model. For the XGBoost model, the hyperparameters include boosting iterations, maximum tree depth, shrinkage, minimum loss reduction, subsample ratio of columns, minimum sum of instance weight, and subsample percentage were tuned. Boosting iterations correspond to the number of boosting rounds or trees to build. Maximum tree depth refers to the maximum number of nodes allowed from the root to the farthest root of a tree. The parameter shrinkage controls the learning rate. The lower value of this parameter makes the model robust against overfitting. Minimum loss reduction parameter is required to make a split. A node is split when the resulting split gives a positive reduction in the loss function. Subsample ratio of columns corresponds to fraction of features (column) to use. Minimum sum of instance weight is required to create a new node in the tree. Subsample percentage corresponds to fraction of observations (the rows) to subsample at each step.

The best model was obtained when boosting iterations is set to 250, maximum tree depth set to 3, shrinkage set to 0.3, minimum loss reduction set to 0, subsample ratio of columns set to 1, minimum sum of instance weight set to 1, and subsample percentage set to 1. Table 4.1 shows the hyperparameter values obtained through a trial-and-error process that were used to evaluate the prediction accuracy of the machine learning models.

Table 4.1 Best Hyperparameter Values for RF and XGBoost

Model	Parameters	Optimal Values
RF	Randomly Selected Predictors	4
XGBoost	Boosting Iterations	250
	Maximum Tree Depth	3
	Shrinkage	0.3
	Minimum Loss Reduction	0
	Subsample Ratio of Columns	1
	Minimum Sum of Instance Weight	1
	Subsample Percentage	1

4.5 Evaluation Metrics

The performance of the models was evaluated using five metrics: accuracy, precision, recall, F1-score, and "Area Under the Curve" (AUC). The equations for the accuracy, precision, recall, and F1-score metrics are shown in Equations 8 to 11.

$$\text{Accuracy} = \frac{TP + TN}{TP+TN+FP+FN} \tag{8}$$

$$\text{Sensitivity/Recall} = \frac{TP}{TP + FN} \tag{9}$$

$$\text{Precision} = \frac{TP}{TP + FP} \tag{10}$$

$$\text{F1-score} = 2 \times \frac{precision \times recall}{precision + recall} \tag{11}$$

where,

TP = True Positive Rate

TN = True Negative Rate

FP = False Positive Rate

FN = False Negative Rate

If a pavement segment's structural condition is poor, and the model correctly predicts this condition, then this is expressed as TP. On the other hand, if the model predicts the structural condition as non-poor, then this is expressed as FN. Similarly, if a pavement segment's structural condition is non-poor, and the model correctly predicts this condition, then this is expressed as TN. Otherwise, this is expressed as FP.

Accuracy can be defined as the percentages of the correctly classified observations over all the observations, which is the most common technique used to determine the prediction accuracy of the model. It can be determined by dividing the number of correctly classified observations by the total number of observations. Recall is the ratio of the correctly classified observations of a particular mode, which can be obtained by dividing the number of correctly classified observations of a particular category by the total number of actual observations of that category. Precision is the ratio of the observations of a particular category that the model has correctly predicted. It is computed by dividing the number of correctly predicted observations of a particular category by the total number of observations of that category. Another important metric that is widely used to measure the classification performance of the machine learning models is Area Under the Curve (AUC) of a Receiver Operating Characteristic (ROC) curve. The higher the AUC value for

a classifier, the better the performance of the machine learning in terms of distinguishing between classifiers. This metric determines the performance of the model based on TP and FP at all classification thresholds. The AUC value above 0.9 indicates the high prediction accuracy of the model while AUC between 0.7 and 0.9 presents moderate accuracy and AUC less than 0.7 means poor prediction accuracy of the model (McDowell, 2006).

CHAPTER 5: RESULTS AND DISCUSSIONS

Tables 5.1 to 5.3 show the prediction accuracy results obtained from the RF, XGBoost, and logistic regression models when they are applied to the test data set. The overall pavement structural condition prediction accuracy of the RF, XGBoost and logistic regression models are 78%, 76%, and 62%, respectively. Thus, both machine learning models outperformed logistic regression. The RF model had a higher sensitivity (78%) than the XGBoost model (76%), indicating that it correctly predicted poor pavement condition for 78% of the segments and misclassified for 22%. In contrast, the XGBoost model accurately predicted pavement condition for 76% of the segments and misclassified for 24%. The RF model also outperformed the XGBoost model in terms precision and F1-score. In terms of AUC, their values for RF, XGBoost, and logistic regression models are 0.811, 0.794, and 0.67, respectively. These results suggest that all three models yield moderately accurate predictions, with RF being the best among the three for the data set used in this study.

Table 5.1 Pavement Structural Condition Prediction Results Using Random Forest

<table>
<tr><th rowspan="4">Predicted Class</th><th rowspan="2"></th><th colspan="2">True Class</th><th rowspan="2">Accuracy</th><th rowspan="2">Sensitivity/ Recall</th><th rowspan="2">Precision</th><th rowspan="2">F1-score</th></tr>
<tr><th>Poor Structural Condition</th><th>Non-poor Structural Condition</th></tr>
<tr><td>Poor Structural Condition</td><td>92</td><td>24</td><td rowspan="2">0.78</td><td rowspan="2">0.76</td><td rowspan="2">0.81</td><td rowspan="2">0.78</td></tr>
<tr><td>Non-poor Structural Condition</td><td>29</td><td>100</td></tr>
</table>

Table 5.2 Pavement Structural Condition Prediction Results Using XGBoost

Predicted Class		True Class: Poor Structural Condition	True Class: Non-poor Structural Condition	Accuracy	Sensitivity/ Recall	Precision	F1-score
	Poor Structural Condition	89	27	0.76	0.74	0.77	0.75
	Non-poor Structural Condition	32	97				

Table 5.3 Pavement Structural Condition Prediction Results Using LR

Predicted Class		True Class: Poor Structural Condition	True Class: Non-poor Structural Condition	Accuracy	Sensitivity/ Recall	Precision	F1-score
	Poor Structural Condition	85	58	0.62	0.70	0.59	0.64
	Non-poor Structural Condition	36	66				

The importance value of each variable can be found from the RF and XGBoost model, which are shown in Table 5.4. As shown, the top three variables that affect a pavement's structural condition are truck percentage, AADT, and pavement age, with truck percentage having higher importance. Both RF and XGBoost models indicated that the soil regions have less effect or explanatory power on a pavement's structural condition.

Table 5.4 Variable Importance Score Using RF and XGBoost

Model	Variable	Importance value
RF	Truck Percentage	100
	AADT	78.82
	Pavement Age	59.04
	Speed Limit	35.89
	Piedmont Region	3.99
	Lower Coastal Plain	3.80
	Middle Coastal Plain	2
	Upper Coastal Plain	0
XGBoost	Truck Percentage	100
	AADT	62.83
	Pavement Age	47.73
	Speed Limit	19.63
	Lower Coastal Plain	2.26
	Piedmont Region	2.04
	Upper Coastal Plain	1.30
	Middle Coastal Plain	0

To determine the robustness of the RF model, the SCI_{12} threshold for poor structural condition was increased (from 3.3) by 10%, 20%, 30%, 40%, and 50%. The overall prediction accuracy and AUC of the RF model are shown in Figures 5.1 and 5.2, respectively. It can be seen that the prediction accuracy fluctuates from 0.76 to 0.79. For AUC, the values fluctuate a bit from case to case, but overall, it remained in a tight range between 0.776 and 0.811. It can be concluded from this analysis that the threshold that divides the dataset into poor and non-poor segments had no effect on the predictive power of the RF model.

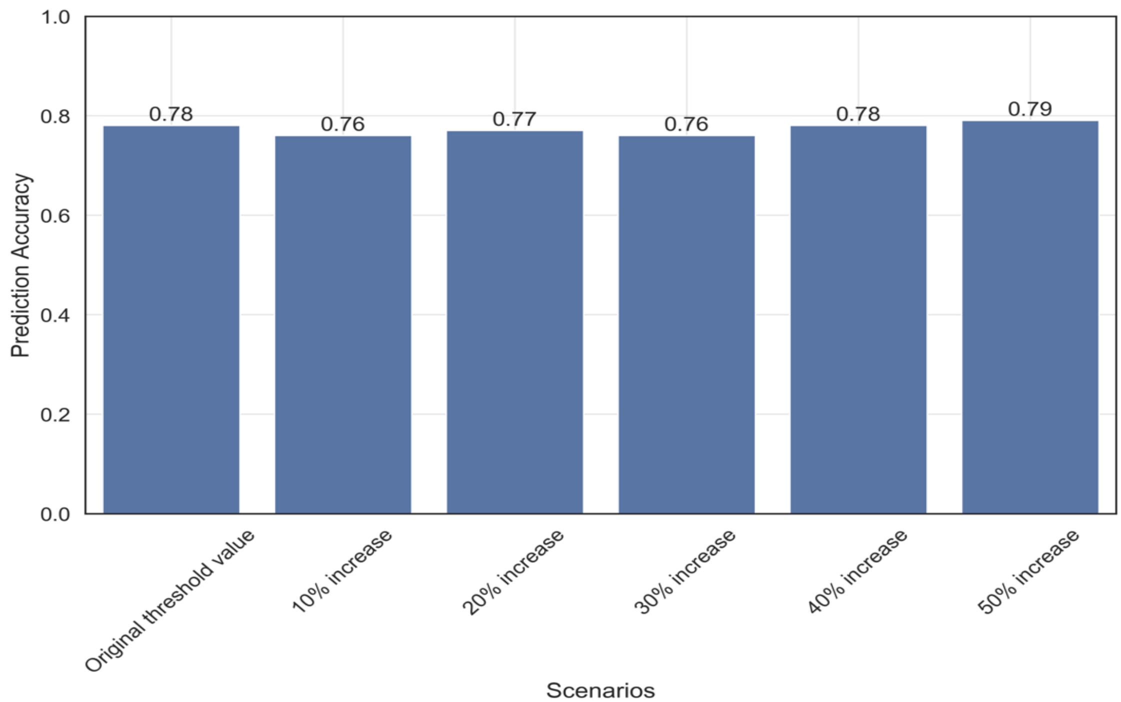

Figure 5.1 Overall prediction accuracy of the RF model

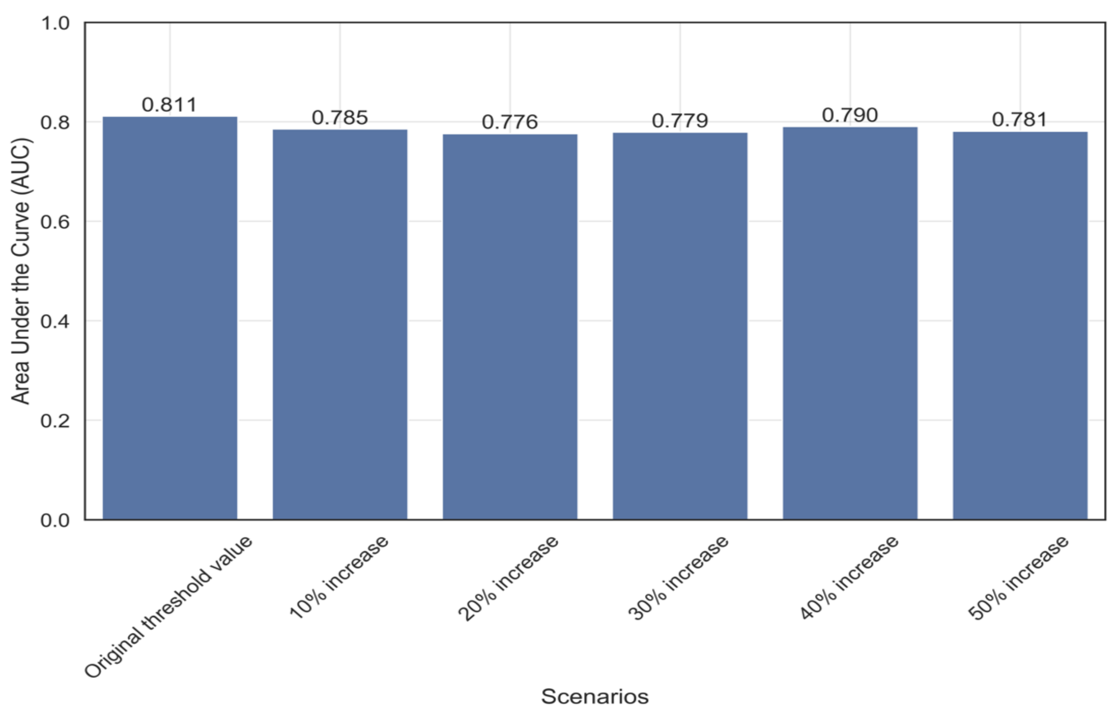

Figure 5.2 AUC of the RF model

CHAPTER 6: SUMMARY AND CONCLUSIONS

Pavement structural condition is an important parameter that is required to be considered for better-informed decision making. As there is little correlation between the pavement structural and functional condition, pavement structural condition cannot be predicted from the pavement functional condition. So, several researchers suggested to consider both pavement structural and functional condition. This thesis proposed the use of machine learning methods to predict the pavement structural condition. This thesis developed two machine learning models, Random Forest (RF) and eXtreme Gradient Boosting (XGBoost), to predict a pavement's structural condition using the explanatory variables: AADT, truck percentage, speed limit, pavement age, and soil regions. When the trained models were applied to the test data set, the results indicated that RF and XGBoost outperformed the logistic regression by 16% and 14%, respectively. The prediction accuracy of the RF model was 2% higher than that of the XGBoost model. Both RF and XGBoost models indicated that truck percentage, AADT, and pavement age significantly influence the pavement's structural condition. The prediction accuracy of the RF model is robust when it was tested using different threshold values that divided the dataset into poor and non-poor pavement segments.

This thesis showed the potential of using machine learning to predict a pavement's structural condition. From the literature review, it is evident that machine learning methods have been widely used in predicting the pavement functional condition. But this is the first

research which developed these types of models to predict the pavement structural condition. A reasonable prediction accuracy was obtained from both models (RF and XGBoost). The results showed that machine learning algorithms can be used for pavement structural condition prediction for they outperformed the traditional logistic regression method.

To make the finding more generalizable, future work should utilize TSD data from several states located throughout the U.S. The key limitations of the thesis are discussed below.

1. The thesis assumed that there is a relationship between the pavement structural condition and the explanatory variables (AADT, truck percentage, speed limit, pavement age, and soil regions. In practice, this may not be the case.

2. Pavement deflection measurements were collected at a particular time of the year. As temperature variations influence the pavement deflection values, temperature correction of the parameter SCI_{12} is required, but not considered in this thesis.

3. This thesis considered only five variables in the machine learning models. Additional variables, such as, temperature, climate condition, and pavement structure data should be explored in future research.

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