Artificial Intelligence (AI) and Markov Process Based Data Mining on Predicting Bridge Operating Conditions

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16. Abstract
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Standard Conversions

SI* (MODERN METRIC) CONVERSION FACTORS				
APPROXIMATE CONVERSIONS TO SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
in	inches	25.4	millimeters	mm
ft	feet	0.305	meters	m
yd	yards	0.914	meters	m
mi	miles	1.61	kilometers	km
		AREA		
in^2	square inches	645.2	square millimeters	mm^2
ft^2	square feet	0.093	square meters	m^2
yd^2	square yard	0.836	square meters	m^2
ac	acres	0.405	hectares	ha
mi^2	square miles	2.59	square kilometers	km^2
		VOLUME		
fl oz	fluid ounces	29.57	milliliters	mL
gal	gallons	3.785	liters	L
ft^3	cubic feet	0.028	cubic meters	m^3
yd^3	cubic yards	0.765	cubic meters	m^3
		NOTE: volumes greater than 1000 L shall be shown in m^3		
		MASS		
oz	ounces	28.35	grams	g
lb	pounds	0.454	kilograms	kg
T	short tons (2000 lb)	0.907	megagrams (or "metric ton")	Mg (or "t")
		TEMPERATURE (exact degrees)		
°F	Fahrenheit	5 (F-32)/9 or (F-32)/1.8	Celsius	°C
		ILLUMINATION		
fc	foot-candles	10.76	lux	lx
fl	foot-Lamberts	3.426	candela/m^2	cd/m^2
		FORCE and PRESSURE or STRESS		
lbf	poundforce	4.45	newtons	N
lbf/in^2	poundforce per square inch	6.89	kilopascals	kPa
APPROXIMATE CONVERSIONS FROM SI UNITS				
Symbol	**When You Know**	**Multiply By**	**To Find**	**Symbol**
		LENGTH		
mm	millimeters	0.039	inches	in
m	meters	3.28	feet	ft
m	meters	1.09	yards	yd
km	kilometers	0.621	miles	mi
		AREA		
mm^2	square millimeters	0.0016	square inches	in^2
m^2	square meters	10.764	square feet	ft^2
m^2	square meters	1.195	square yards	yd^2
ha	hectares	2.47	acres	ac
km^2	square kilometers	0.386	square miles	mi^2
		VOLUME		
mL	milliliters	0.034	fluid ounces	fl oz
L	liters	0.264	gallons	gal
m^3	cubic meters	35.314	cubic feet	ft^3
m^3	cubic meters	1.307	cubic yards	yd^3
		MASS		
g	grams	0.035	ounces	oz
kg	kilograms	2.202	pounds	lb
Mg (or "t")	megagrams (or "metric ton")	1.103	short tons (2000 lb)	T
		TEMPERATURE (exact degrees)		
°C	Celsius	1.8C+32	Fahrenheit	°F
		ILLUMINATION		
lx	lux	0.0929	foot-candles	fc
cd/m^2	candela/m^2	0.2919	foot-Lamberts	fl
		FORCE and PRESSURE or STRESS		
N	newtons	0.225	poundforce	lbf
kPa	kilopascals	0.145	poundforce per square inch	lbf/in^2

*SI is the symbol for the International System of Units. Appropriate rounding should be made to comply with Section 4 of ASTM E380.
(Revised March 2003)

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Executive Summary

To facilitate bridge management decision-making and implement preventive maintenance strategies, we endeavor to develop a machine learning model to predict the future condition rating of bridges using historical inspection data, with a funding contract with Connecticut State's Department of Transportation. We collect the data from the USA's National Bridge Inventory (NBI) about the nation's bridges, including their location, design, condition, and usage. We process, reformat and transform the collected datasets (1992-2021) so that the machine learning model can be trained to predict the bridge conditions over the future 100 years. During the data processing, we tackle the challenges associated with predicting bridge condition ratings, such as dealing with heterogeneous data sources, handling complex high-dimensional data, and incorporating mixed types of data features. Also, we address the need for feature selection and long-term prediction capabilities. To meet these challenges, we propose a comprehensive framework based on deep neural networks, which enables us to effectively predict future 100-year bridge condition ratings based on the historical data from 1992-2021. Our approach utilizes all inspection features used for bridge condition rating. We employ an autoencoder neural network to compress the high-dimensional categorical features, and a long short-term memory (LSTM) recurrent neural network (RNN) to compress the high-dimensional sequential data into lower-dimensional latent features. The latent features obtained from the pre-trained autoencoder, and LSTM networks serve as inputs to a multi-layer perceptron (MLP) network for the final bridge condition rating prediction. We adopt a two-stage training process, wherein the autoencoder, LSTM, and MLP networks were trained and tuned separately. The final pre-trained model is then applied to perform a comprehensive study of predicting the condition rating of all bridges in Connecticut. All the results predicted are organized in the deterioration trends of all bridges, the deterioration curves of individual bridges and the bridges with potential risks.

CHAPTER 1 INTRODUCTION

1.1 Background

Bridges play a vital role in maintaining the efficiency of road networks within an infrastructure system and must undergo regular inspections to ensure public safety. In the United States, bridges are typically inspected once every two years to assess their overall condition. These inspections focus on key components such as the deck, superstructure, and substructure. A comprehensive range of factors is considered during the inspection process, including bridge type, materials, geometry, and design. These factors remain constant and are presented in a tabular format. Temporal factors like average daily traffic (ADT), bridge ratings, and temperature are also taken into account, as they vary over time and are evaluated sequentially.

The USA's National Bridge Inventory (NBI) serves as a comprehensive database that houses detailed information about the nation's bridges, including their location, design, condition, and usage. One crucial aspect of the NBI focuses on evaluating the condition of each bridge. This evaluation involves inspections carried out by bridge engineers, who provide ratings indicating the structural condition and functional adequacy of the bridge. Such information is invaluable in prioritizing maintenance, repairs, and rehabilitation efforts, ensuring the safety and reliability of the overall bridge network. The condition of a bridge, whether it pertains to the entire structure or specific key components, is assessed on a scale of 0 to 9, encompassing conditions ranging from Failed, Imminent Failure, Critical, Serious, Poor, Fair, Satisfactory, Good, Very Good to Excellent (*FHWA 1995*).

According to the Infrastructure Report Card 2021 (*www.infrastructurereportcard.org*), there are more than 617,000 bridges across the United States. Currently, 42% of all bridges are at least 50 years old, and 46,154, or 7.5% of the nation's bridges, are considered in poor condition, meaning that at least one component is in poor condition and requires rehabilitation or replacement. Unfortunately, 178 million trips are taken across these structurally deficient bridges every day. A recent estimate for the nation's backlog of bridge repair needs is $125 billion. At the current rate of investment, it will take until 2071 to make all of the repairs that are currently necessary, and the additional deterioration over the next 50 years will become overwhelming.

To facilitate bridge management decision-making and implement preventive maintenance strategies, significant efforts have been devoted to modeling the condition of bridges using historical inspection data, enabling the prediction of future condition ratings. Classical methods such as linear or nonlinear regression have been employed to establish the relationship between the condition rating and inspection features (*Marcous et al. 2002*). However, these regression techniques face challenges posed by the characteristics of bridge inspection data, including imbalanced distribution of records (e.g., far fewer bridges with low ratings)), missing and erroneous data entries, and the subjectivity inherent in manual inspection processes.

To address these challenges, researchers have utilized Markovian chain modeling to capture the stochastic nature of bridge deterioration. This approach considers the current condition rating of a bridge as a state and probabilistically transitions it to future states over time. By incorporating this probabilistic framework, it aims to account for random variations in subjective inspections and uncertainties associated with certain inspection features (*Cesare and Santamarina 1992*, *Gora 2023*). However, this probabilistic state transition has traditionally been performed year by year, without taking into account any memory of short or long-term historical data.

With the availability of historical bridge inspection data and advancements in machine learning (ML) techniques, ML-based models for predicting bridge condition deterioration have been developed since the 1990s. *Cattan and Mohammadi 1997* pioneered the use of a neural network system to establish the relationship between subjective bridge condition ratings and bridge parameters. They applied this approach to railroad bridges within the commuter rail system of the Chicago metropolitan area. The study included 405 bridges, utilizing 12 structural parameters as inputs and the subjective bridge rating as the output. During the implementation of the model, a binary code consisting of 4 bits was employed to represent the bridge ratings. Similarly, a binary code with 4 bits was used to define the bins of the histogram for each input variable. As a result, the neural network configuration comprised 45 neurons in the input layer, two hidden layers with 45 neurons each, and 4 neurons in the output layer.

After uncovering the shortcomings of the Markovian model in effectively capturing the stochastic progression of deterioration, *Huang 2010* employed statistical analysis to identify 11 influential factors that impact the deterioration of bridge decks in Wisconsin. Subsequently, an Artificial Neural Network (ANN) model was developed to estimate the future condition of these bridge decks. The prediction model utilized various influential features as inputs, including maintenance, age, previous condition, and eight significant inventory attributes. The ANN architecture implemented was a five-layer Multi-Layer Perceptron (MLP) with five hidden neurons present in each hidden layer.

Li and Burgueno 2010 employed artificial neural networks (ANNs) and fuzzy logic to extract historical patterns from the National Bridge Inventory (NBI) data. They aimed to develop damage prediction models specifically for bridge abutment walls, utilizing the extensive NBI database. The developed model consisted of an ensemble of five parallel neural networks: Multi-layer Perceptron (MLP), Radial Basis Function (RBF), Support Vector Machine (SVM), Supervised Self-Organizing Map (SSOM), and Fuzzy Neural Network (FNN). Structural parameters served as the input to the model, while the output was the structural condition. Predictions were generated by aggregating and combining the results of the individual networks through a voting mechanism. This approach effectively addressed the challenges associated with biased and unbalanced databases, resulting in improved prediction accuracy.

Creary et al. 2012 utilized bridge inspection data provided by the Connecticut Department of Transportation to develop a Multi-layer Perceptron (MLP) model for predicting the future operating condition of bridges. The model incorporated 21 inputs encompassing information related to geometry, construction, and service. The output variables consisted of condition ratings for the deck, superstructure, and substructure. Through the analysis performed using the trained model, the researchers identified the most influential variables (inputs). The top four variables were deck treatment, last deck condition, last inspection date, and year built. In another study, *Tokdemir et al. 2000* utilized two artificial intelligence (AI) tools, namely Artificial Neural Networks (ANN) and Genetic Algorithms (GA), to develop models for predicting bridge sufficiency ratings. The models were developed using current geometrical, age, traffic, and structural attributes as explanatory variables. The data used for this analysis was acquired from the California Department of Transportation, which included 19,120 structural bridge components. A simple multi-layer neural network with backpropagation was employed, featuring 28 input features and one output feature. Additionally, *Ali et al. 2019* developed an ANN model for predicting bridge conditions. In this study, 15 relevant properties associated with the condition of bridges were selected as inputs, while three conditions were defined as the outputs. The results obtained from the ANN model were compared with those obtained from a linear regression model, serving as a benchmark for evaluation.

Lim and Chi 2019 conducted a study using data from the Korean Bridge Management System to estimate the condition of bridges at different damage levels. The analysis considered various influencing factors for seven different types of damage across six main structure types. To achieve this, they employed the Extreme Gradient Boosting (XGBoost) method, which offers the advantage of not assuming determinacy and independence. The study generated 36 decision trees, yielding significant performance measures. By utilizing the Shapley Additive Explanation (SHAP) value, the study identified the major factors that influence damage to bridges. These factors included age, average daily truck traffic, vehicle weight limit, total length, and effective width. The dataset used in the study comprised 443,553 records obtained from 10,187 detailed inspections, along with precise safety diagnoses for 2,388 bridges constructed in Korea between 1966 and 2016. The inspections were conducted from 2003 to 2016.

Liu and Zhang 2020 presented a novel approach that employed a convolutional neural network (CNN) trained on National Bridge Inventory (NBI) data to predict the future condition of bridge components. The model assumed that there would be no significant condition improvement work in the near future, while routine maintenance or minor repairs were still considered. To illustrate the effectiveness of their proposed method, a case study was conducted on Maryland and Delaware highway bridges using historical data spanning from 1992 to 2017. In this particular CNN model, 24 influential features were incorporated, and the bridge ratings were limited to a range between 3 and 9. It is important to note that the NBI dataset considered in this study had a scarcity of samples with condition ratings below 3. It should be acknowledged that the assumption that a bridge will not undergo future repairs or rehabilitation may not hold true in practice, and this assumption requires further examination.

Liu and El-Gohary 2022 introduced a deep learning-based method for predicting bridge deterioration by leveraging heterogeneous structured data from sources like the National Bridge Inventory (NBI), National Bridge Elements (NBE), structured traffic and weather data, and unstructured textual bridge inspection reports. Their proposed approach incorporated manifold learning techniques to embed high-dimensional and sparse data into a low-dimensional dense space. Additionally, cost-sensitive learning was employed to address data imbalances, and a Recurrent Neural Network (RNN) was utilized to learn from past years' integrated bridge data and predict the conditions of primary bridge components for the subsequent year. To evaluate the performance of their prediction model, the researchers tested it using bridge data from the state of Washington. While this study provided a comprehensive approach within the realm of deep learning models, it did not differentiate between tabular features and sequential features during model development. Additionally, the RNN employed in the study was only effective for short-term memory, posing challenges when attempting to retain information from decades of inspection data.

1.2 Objectives of the Project

Bridge Management Systems (BMS) has been an important tool for state agencies managing bridge networks to formulate maintenance and inspection programs within cost limitations. Prediction of future bridge condition ratings is a fundamental component of the BMS. A reliable bridge management program depends on how accurately the ratings of the bridge components can be estimated. This project aimed to develop an artificial intelligence (AI) based data mining method for estimating bridge future conditions and the deterioration process. The proposed method can also be used to identify the impact of the most influencing parameters on the degradation of bridge structures.

There were three major objectives for this research: 1) Build upon previous research to extend and refine the Artificial Neural Networks (ANN) model to provide more accurate bridge condition predictions; 2) integrate ANN with Markov process to achieve more reliable probabilistic prediction; and 3) facilitate bridge asset management and bridge inspection process in the Bridge Management System (BMS).

The proposed research applies artificial neural networks to a larger database over a longer duration i.e., 15 ~ 20 years of bridge inspection in Connecticut. It is expected that additional data extending the time range of inspections can help produce more accurate and nuanced predictions A series of experiments with varying ANN architectures and hyperparameters were conducted to produce an optimally trained model appropriate for the Connecticut bridge inspection database. Second, the research integrates ANN results with Markov process to create deterioration curves. Clustering data by significant influencing variables such as the era of construction and percentage of heavy vehicles helped get more reliable results. Third, results obtained through this study are used in the bridge assessment management and inspection process to enable more effective design and management of bridges in the BMS.

The scope of research includes the use of artificial neural networks to predict bridge operating conditions and the results are incorporated with a Markov process to model the deterioration of bridges. The deterioration models are validated using a full set of condition data collected by the Connecticut Department of Transportation. The predictions are focused on the overall and level performance of bridges including deck, superstructure, and substructure components. Culvert condition and channel protection prediction are not part of this research.

CHAPTER 2 DATA COLLECTION AND DATA PROCESSING

2.1 NBI Dataset and Features

The NBI dataset is maintained by the FHWA, and is publicly available on an as-is basis. This dataset contains data collected from bridge inspections across the United States and is available for every year and state starting from 1992. Any single datasheet has 124 to 135 features. Most of these features are documented with detailed descriptions on the NBI dataset reference manual (FHWA 1995). At the beginning of our project, we took some time to go through the manual and thoroughly understand each feature, then we grouped the features into categories. These groups and their corresponding feature counts are as follows:

1. Location features, provide details about the location of bridges, totaling 49 features.
2. Management/Operation features are used by the DOT to record the management or operating status of a bridge and consist of 2 features.
3. Roadway Design features define the initial design parameters for roadways where the inventory bridge is situated, comprising 28 features.
4. Bridge Material category, containing two features that focus on the structural materials used in the bridge.
5. Bridge Geometry category, encompassing 10 features, pertains to the geometric aspects of the bridge's structure.
6. Bridge Other Design category includes features related to hydraulics, navigation, or geotechnical considerations of the bridge, totaling 5 features.
7. Roadway Inspection category, comprising 5 features, contains inspection data regarding the condition of the roadway.
8. Bridge Inspection category contains 8 features and provides data on the condition of the bridge's structure.
9. Other Inspection category consists of 2 features, including condition ratings of the bridge not covered in the previous inspection categories.
10. Bridge Rating category contains 5 features with rating results for the bridge's structural components.

11. Other Rating category, with 4 features, contains rating results for other non-structural elements of the bridges.
12. Reconstruction Data category comprises 8 features discussing proposed reconstruction work and associated costs.

Success in analyzing the NBI dataset depends heavily on data cleaning and feature engineering. The data cleaning step is often cumbersome, and not highly technical; therefore, it is often overlooked. For the sake of completeness, this section summarizes a few lessons learned in the data cleaning process and gives perspective on the complexity of this dataset. To summarize the data exploration and data cleaning step, we broke down the process into the following steps: data extraction, data filtering, data transformation, data exploration, and data cleaning. Figure 1 depicts the data process procedure used in the project.

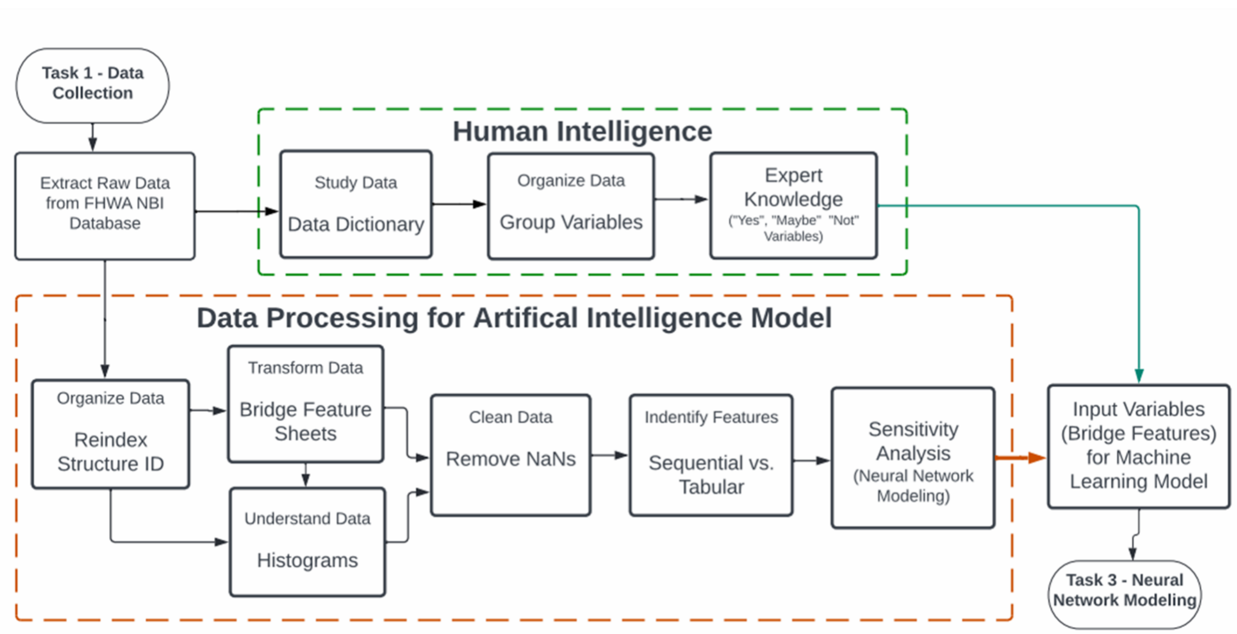


Figure 1 Data Processing Procedure

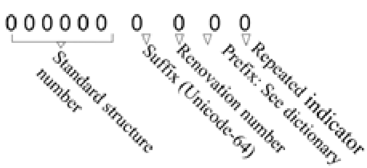
2.2 Data Extraction

Using an automated script, we extracted all of the historic data from 1992 to 2021 for the six New England states from the FHWA NBI records repository: Connecticut (CT), Maine (ME), Massachusetts (MA), New Hampshire (NH), Vermont (VT), and Rhode Island (RI). Then we employed a preliminary filtering process which eliminated bridges from the data set that had been recorded for less than five years and features that had not been recorded for the duration of the study. This decision was made with the foresight that our predictive model would need at least five years of history of a bridge as an input.

2.3 Unifying the Structure Numbering

In the raw data (1992-2021) the structure numbers come in different formats, as shown in the first column of Table 1 below. To unify the numbering format, we created a rule and reindexed the structure number while keeping the original data unchanged.

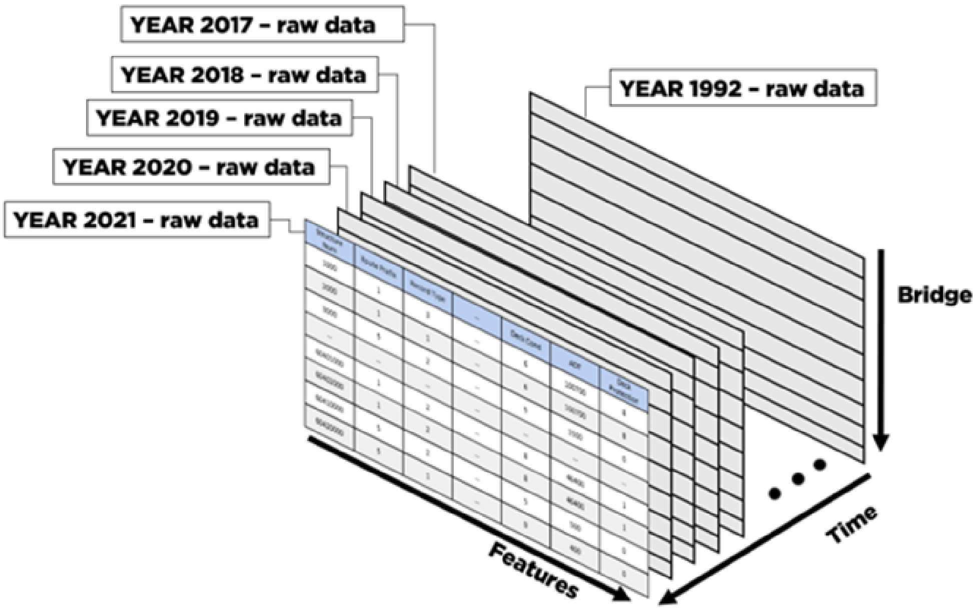
Table 1 Structure Number, Original vs Reindexed



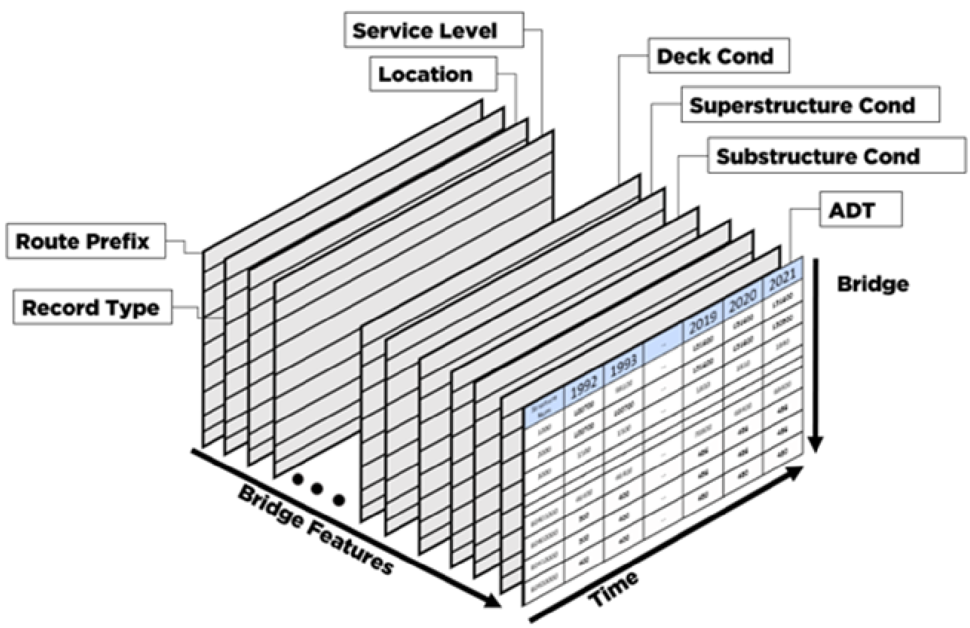
ORIGINAL STRUCTURE NUMBER	FORMATTED STRUCTURE NUMBERS
00001	10000
00002	20000
03406A	34061000
03406B	34062000
03407	34070000
03408	34080000
0000S50020B4071	40710020
0000S50020B4072	40720020
CEPNEDCT0910003	100030010
CEPNEDCT0910004	100040010

2.4 Data Transformation

Data transformation was done in multiple steps however, the first type of data transformation employed was to combine all the discrete data tables into tables that carry a bridge's information through time, this process was described more in-depth by *Liu and Zhang 2020*. Figure 2 below depicts the raw data with the format given by the dataset, in this format, each sheet only contains one year's information. Table 2 gives the Year 1992 sample. Therefore, we transformed the dataset so that each sheet now contained information over multiple years. This required that bridge numbers did not change over time, and if any bridge was not present for a given year's datasheet the information for that bridge for that year would be filled in as a null value, and then revisited in the data cleaning step.



(a) Before transformation



(b) After transformation

Figure 2 Datasheets before transformation (a), and after transformation (b)

Table 2 Raw Data Sample - Year 1992

Structure Num	Route Prefix	Record Type	...	Deck Cond	ADT	Deck Protection
1000	1	3	...	6	100700	8
2000	1	1	...	6	100700	8
3000	5	2	...	5	1500	0
...	...	...	...	...	...	...
60401000	1	2	...	8	46400	1
60402000	1	2	...	8	46400	1
60410000	5	2	...	5	500	0
60420000	5	1	...	0	400	0

2.5 Understanding the Data

The importance of thoroughly understanding your data before data cleaning cannot be overemphasized. The data exploration stage yielded the knowledge necessary for the data cleaning step, which allowed us to make informed decisions on how to handle missing values, or non-numerical values. The end goal of this process was to produce fully defined, numerical datasets for a neural network model.

Tables 3 and 4 show samples of the bridge features categorized in tabular and sequential features. Tabular features are those varying less with time and sequential features are those varying frequently with time.

Table 3 Bridge Feature Sheet Sample - Route vs Time, Tabular Feature

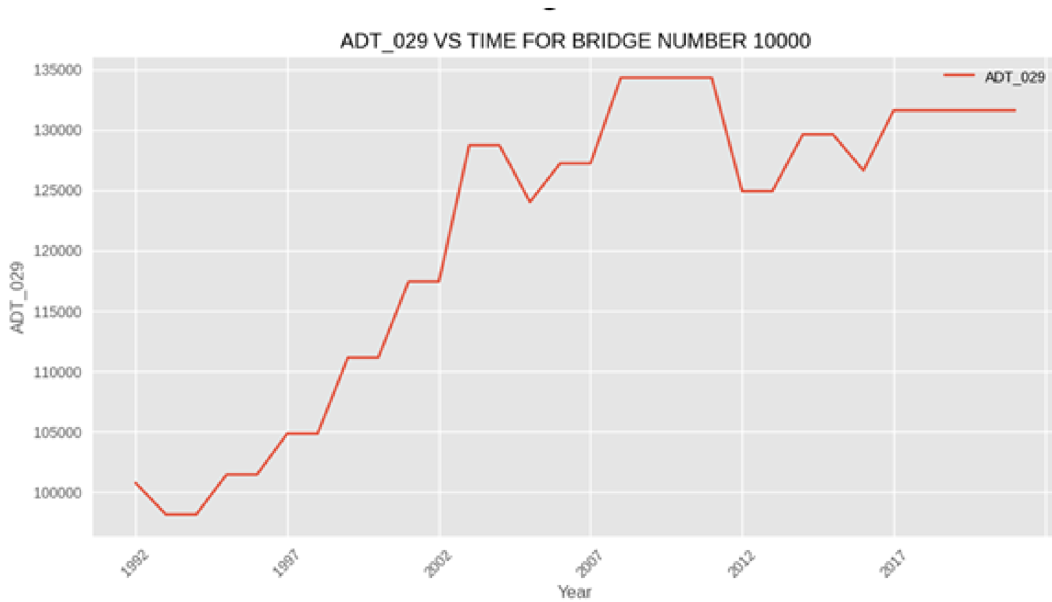
Structure Num	1992	1993	...	2019	2020	2021
1000	1	1	...	1	1	1
2000	1	1	...	1	1	1
3000	5	5	...	5	5	5
...	...	...	...	...	...	...
60401000	1	1	...	1	1	1
60402000	1	1	...	1	1	1
60410000	5	5	...	5	5	5
60420000	5	5	...	5	5	5

Table 4 Bridge Feature Sheet Sample - ADT vs Time, Sequential Feature

Structure Num	1992	1993	...	2019	2020	2021
1000	100700	98100	...	131600	131600	131600
2000	100700	100700	...	131600	131600	130800
3000	1500	1500	...	1810	1810	1840
...	...	...	...	...	...	...
60401000	46400	46400	...	70800	68400	68400
60402000	500	400	...	486	486	486
60410000	500	400	...	486	486	486
60420000	400	400	...	480	480	480

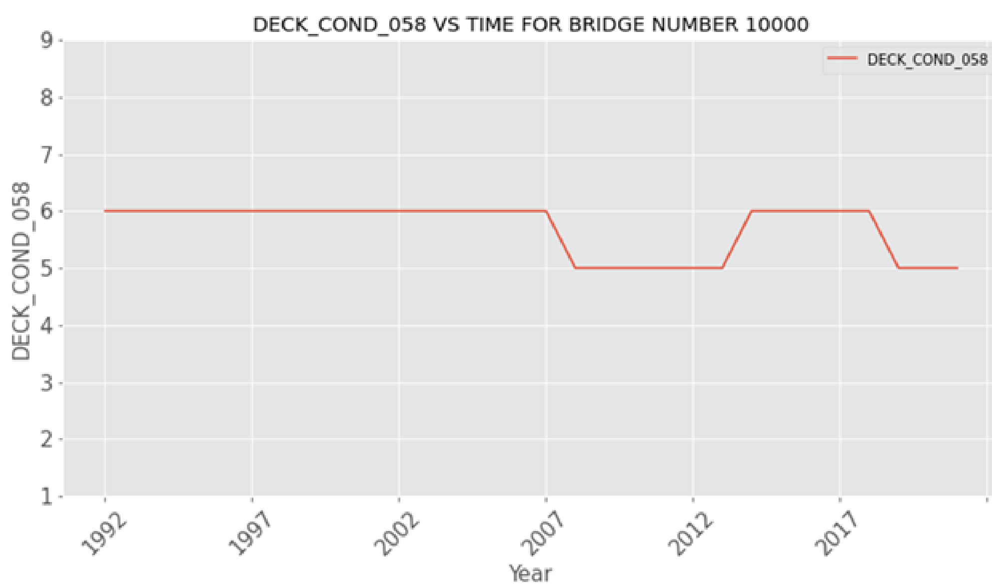
Figures 3 to 6 show sample results of our data understanding for a particular bridge, such as feature changing over time, bridge rating changing over time, bridge receiving rehabilitation at a time, the life expectancy etc.

As a sample, Figures 7and 8 show statistics of various information on the bridges in the database, for the years built, for the types and materials of the bridges, and for the deck condition rating, respectively. Figure 9 reveals the relationship in statistics among ADT, year built and deck rating in Pari plot.



(a) ADT Changes Over Years

(b)



(a) Deck Condition Changes Over Years

Figure 3 Bridge Trend Over Years, Bridge ID 10000

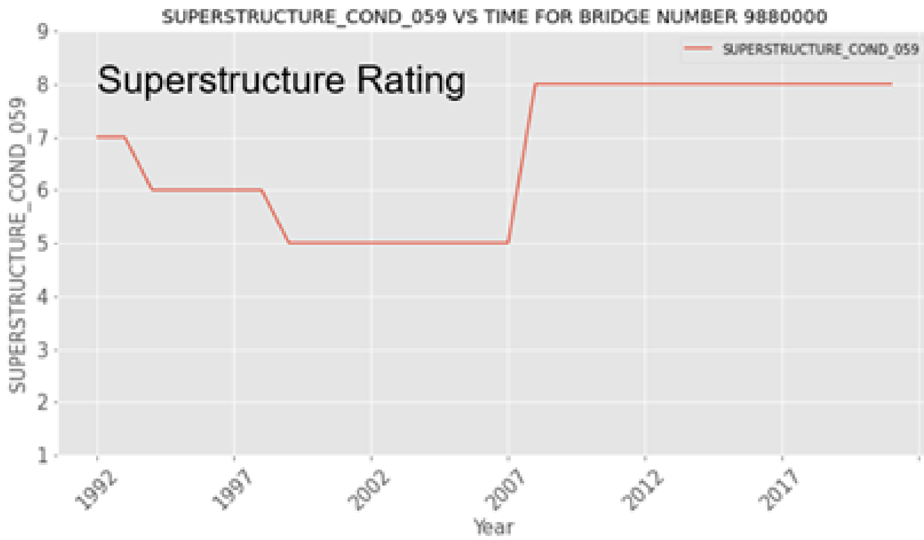


Figure 4 Bridges Possibly Receiving Rehabilitation

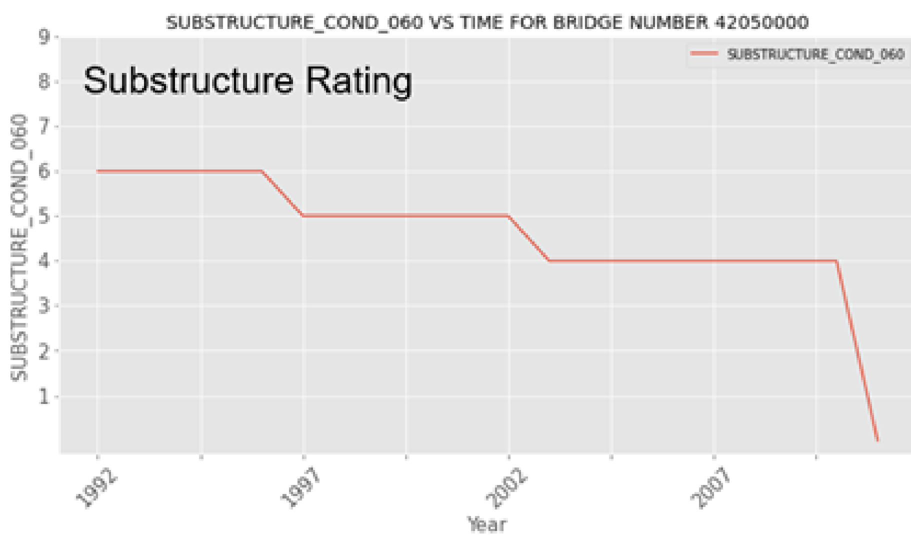


Figure 5 Bridges with Shorter Life

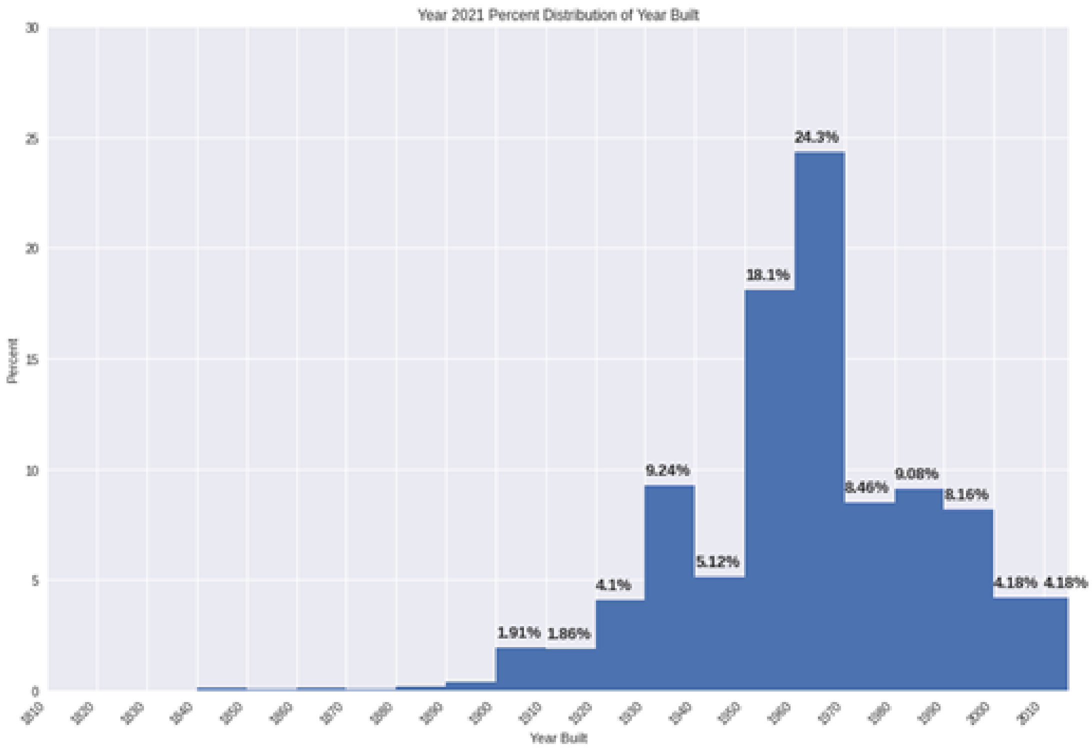


Figure 6 YEAR BUILT OF BRIDGES IN 2021

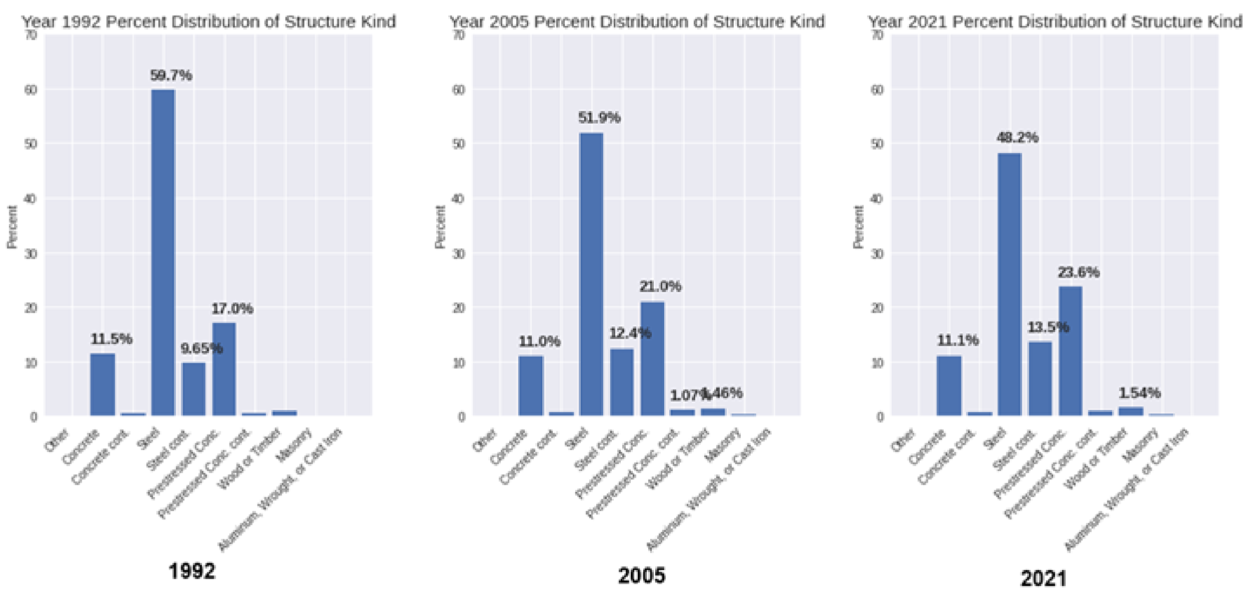


Figure 7 STRUCTURE KIND AND MATERIALS

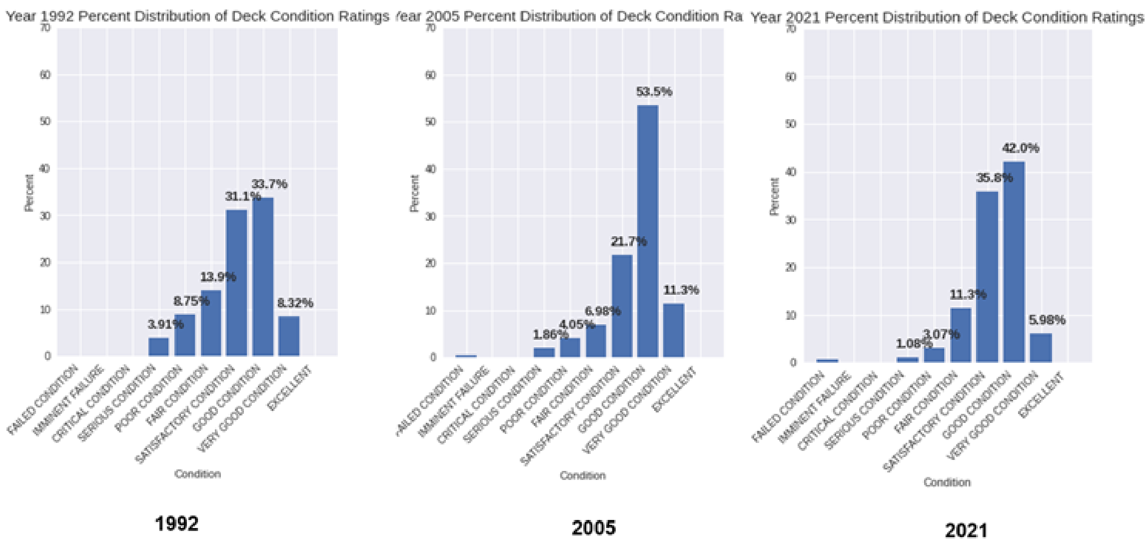


Figure 8 DECK CONDITION RATING

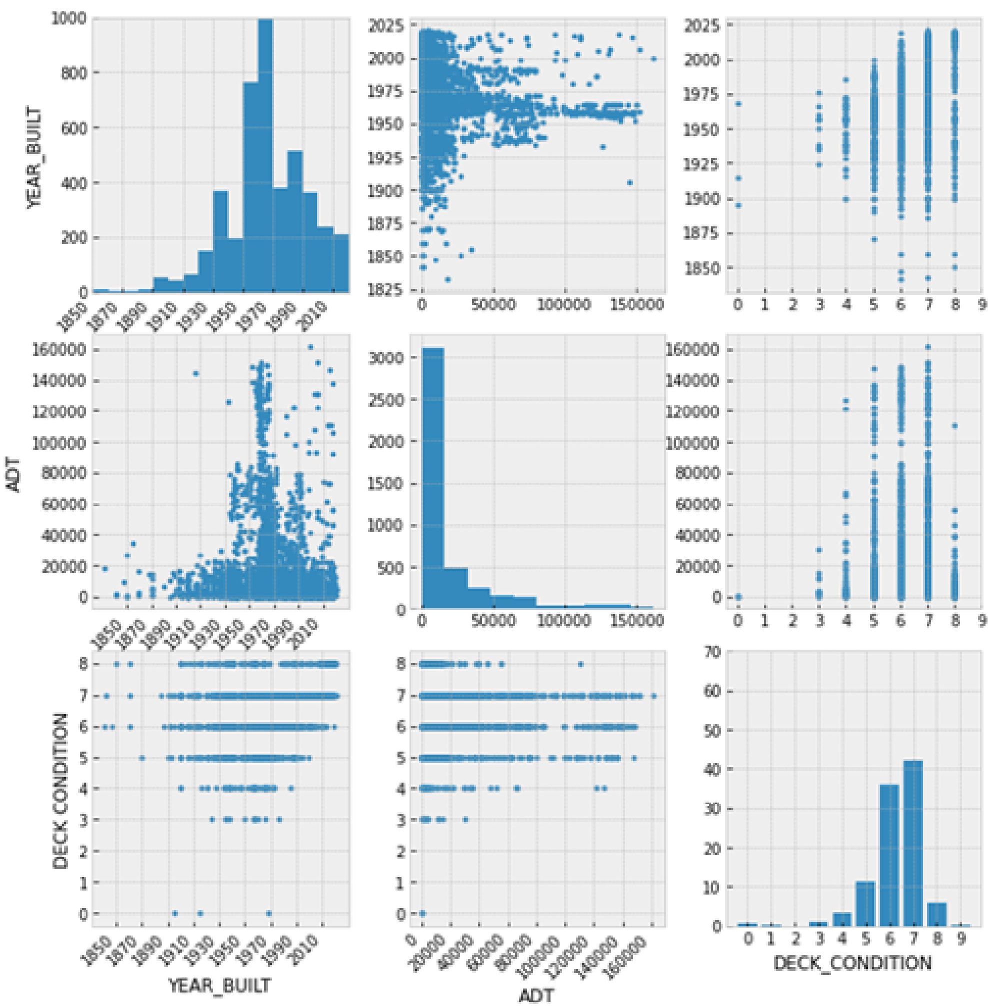


Figure 9 Pari Plots of Year Built, ADT and Deck Rating

2.6 Data Cleaning

Different data cleaning techniques were used to remove all null and values while removing as few features from the dataset as possible. First each feature was evaluated to see if the null values could easily be replaced by a new value that did not affect the meaning of the feature. For example, if a feature is categorical, and null values mean that the feature does not apply to a bridge, then those null values may be replaced by a new category that simply implies that the feature does not apply to the bridge. Since this feature is categorical, then adding a new category does not affect the others. On the other hand, if the feature is numerical, like bridge length, then replacing the null values by another value would not only imply something that we do not know it is true, but it would also change the distribution of that feature, which in turn would affect all the other bridges.

The next consideration was whether the feature was only defined for bridges that fall under the scope of the project. For example, culverts, although they are considered bridges under the NBI guidelines, are not the main concern of our network, therefore these bridges were eliminated, and the feature was kept. On the other hand, if the feature is only defined for bridges outside our scope, then the feature was removed.

Finally, we separated the features between tabular and sequential features, this process is described in a later paragraph. Once separated we applied different techniques to eliminate the remaining null values. With the tabular features we took the most frequent non-null value over each bridge's lifetime. Whereas for sequential features, we substituted null values with the next value seen for that bridge, if there is none then we substitute with the last value seen. After implementing these data cleaning steps, few null values remained, and the ones that did could be attributed to errors in data entry, therefore these bridges were removed from the dataset.

Figure 10 depicts the framework used for data cleaning.

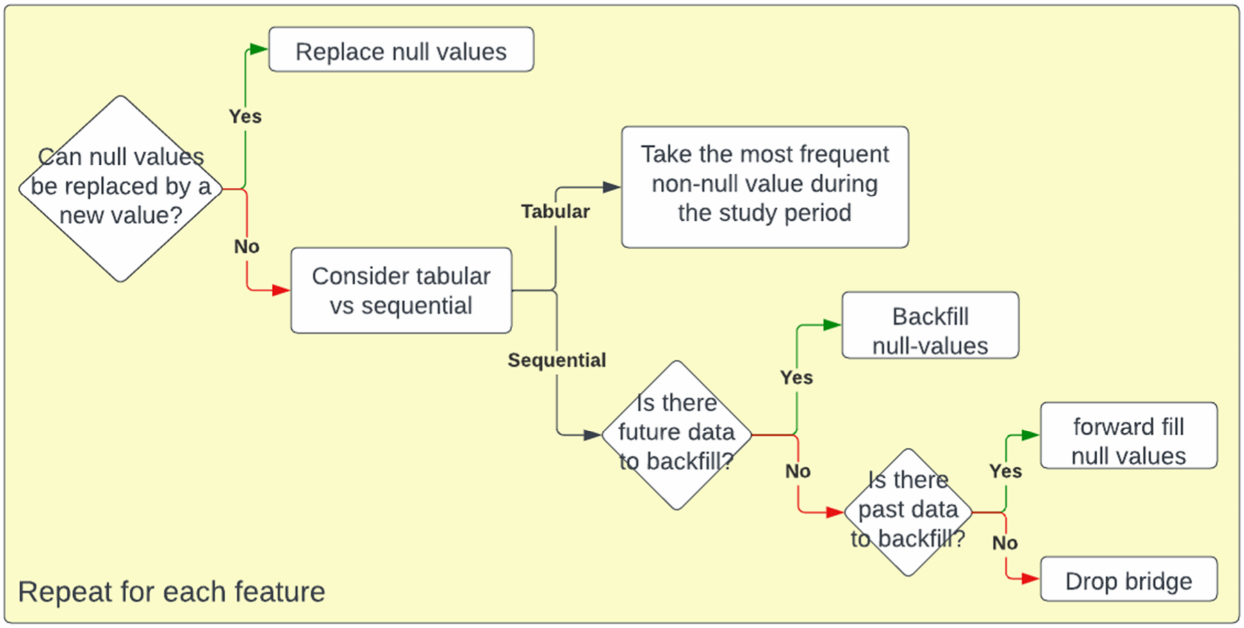


Figure 10 FRAMEWORK FOR DATA CLEANING PROCESS

2.7 Identifying Tabular Features and Sequential Features

Tabular features are those that are not affected by time, e.g., the material of a bridge, while sequential features are those that are affected by time, e.g., the age of the bridge. The framework (Figure 11) used to categorize tabular versus sequential features was procedural, however it also required human judgement. As shown in Figure 12, the first way that the features were subdivided was by setting a threshold, h, and then for each feature, counting the number of times that this feature changed for each bridge over the 30 year study period. If more than 50% of bridges had more than h changes for a given feature then that feature would be categorized as sequential, and vice versa, if less than 50% of bridges had more than h changes for a given feature then that feature would be categorized as tabular. This procedure was repeated with different values of h before arriving at a final value that we believed correctly categorized the features; However, this procedure, although useful, appeared to be problematic with this dataset. Because some features such as the condition ratings were categorized as tabular, even though these were known to be sequential. For this reason, some human judgement was introduced to arrive at the final categorization of tabular vs sequential features.

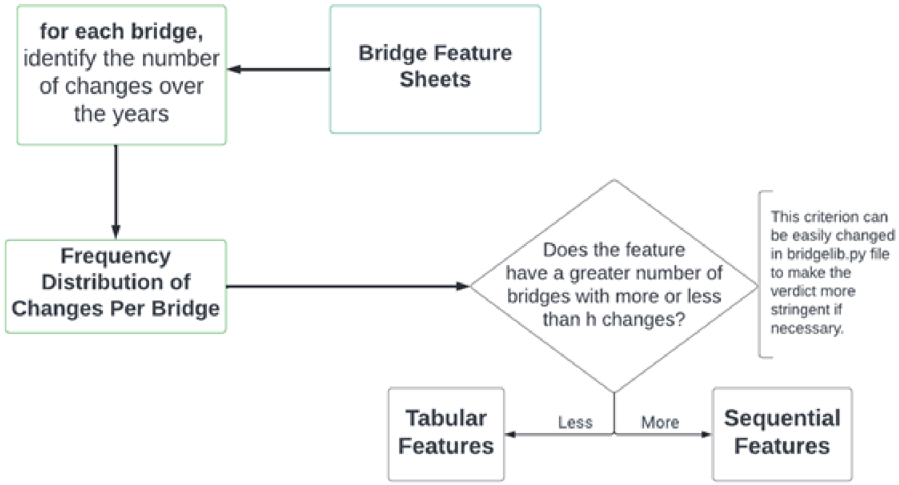


Figure 11 The Procedure to Identify Tabular and Sequential Features

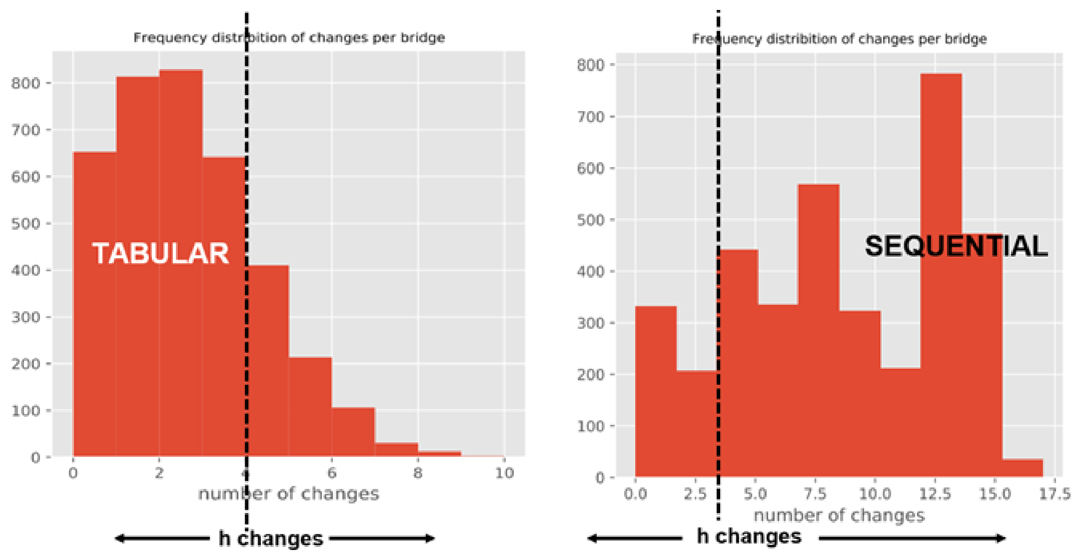


Figure 12 The Discriminant for Tabular and Sequential Features

2.8 Results of Data Processing

The number of bridges in the database varied per year. Some bridges were only recorded for some years but then ceased being recorded, other bridges that were not added to the database until after 1992. The number of unique recorded NBI bridges for CT, ME, MA, NH, VT, RI are 4361, 2485, 5245, 2527, 2789, and 779 respectively. The number of features on our dataset after data cleaning was equal to 84 tabular features, and 12 sequential features, as given in Table 5 and 6.

Table 5 List of Tabular Features

List of Tabular Features					
ROUTE_PREFIX_005B	FUNCTIONAL_CLASS_026	NAV_VERT_CLR_MT_039	RIGHT_CURB_MT_050B	POSTING_EVAL_070	TRAFFIC_DIRECTION_102
SERVICE_LEVEL_005C	YEAR_BUILT_027	NAV_HORR_CLR_MT_040	ROADWAY_WIDTH_MT_051	WATERWAY_EVAL_071	FEDERAL_LANDS_105
ROUTE_NUMBER_005D	TRAFFIC_LANES_ON_028A	OPEN_CLOSED_POSTED_041	DECK_WIDTH_MT_052	APPR_ROAD_EVAL_072	YEAR_RECONSTRUCTED_106
HIGHWAY_DISTRICT_002	TRAFFIC_LANES_UND_028B	SERVICE_ON_042A	VERT_CLR_OVER_MT_053	WORK_PROPOSED_075A	DECK_STRUCTURE_TYPE_107
COUNTY_CODE_003	DESIGN_LOAD_031	SERVICE_UND_042B	VERT_CLR_UND_054B	WORK_DONE_BY_075B	SURFACE_TYPE_108A
PLACE_CODE_004	APPR_WIDTH_MT_032	STRUCTURE_KIND_043A	LEFT_LAT_UND_MT_056	INSPECT_FREQ_MONTHS_091	MEMBRANE_TYPE_108B
FEATURES_DESC_006A	MEDIAN_CODE_033	STRUCTURE_TYPE_043B	DECK_COND_058	FRACTURE_092A	DECK_PROTECTION_108C
FACILITY_CARRIED_007	DEGREES_SKEW_034	APPR_KIND_044A	SUPERSTRUCTURE_COND_059	SPEC_INSPECT_092C	PERCENT_ADT_TRUCK_109
LOCATION_009	STRUCTURE_FLARED_035	APPR_TYPE_044B	SUBSTRUCTURE_COND_060	BRIDGE_IMP_COST_094	NATIONAL_NETWORK_110
MIN_VERT_CLR_010	RAILINGS_036A	MAIN_UNIT_SPANS_045	CHANNEL_COND_061	ROADWAY_IMP_COST_095	PIER_PROTECTION_111
LONG_017	TRANSITIONS_036B	APPR_SPANS_046	OPR_RATING_METH_063	TOTAL_IMP_COST_096	BRIDGE_LEN_IND_112
DETOUR_KILOS_019	APPR_RAIL_036C	HORR_CLR_MT_047	OPERATING_RATING_064	YEAR_OF_IMP_097	
TOLL_020	APPR_RAIL_END_036D	MAX_SPAN_LEN_MT_048	INV_RATING_METH_065	OTHER_STATE_CODE_098A	
MAINTENANCE_021	HISTORY_037	STRUCTURE_LEN_MT_049	INVENTORY_RATING_066	OTHER_STATE_PCNT_098B	
OWNER_022	NAVIGATION_038	LEFT_CURB_MT_050A	DECK_GEOMETRY_EVAL_068	STRAHNET_HIGHWAY_100	

Table 6 List of Sequential Features

List of Sequential Features
LAT_016
ADT_029
YEAR_ADT_030
LAT_UND_MT_055B
STRUCTURAL_EVAL_067
DATE_OF_INSPECT_090
SCOUR_CRITICAL_113
FUTURE_ADT_114
YEAR_OF_FUTURE_ADT_115

Incorporate Human Input

ADT_029
YEAR_ADT_030
STRUCTURAL_EVAL_067
DATE_OF_INSPECT_090
SCOUR_CRITICAL_113
FUTURE_ADT_114
YEAR_OF_FUTURE_ADT_115
DECK_COND_058
SUPERSTRUCTURE_CON_059
STRUCTURE_CON_060
TEMPERATURE
FREEZE-THAW CYCLE DAYS
HUMIDITY
WIND SPEED
PERCIPITATION
SNOW FALL

CHAPTER 3 ARTIFICIAL NEURAL NETWORK MODELLING

3.1 The Framework

The proposed Neural Network model (Figure 13) consists of three primary components: a pre-trained undercomplete autoencoder neural network, a pre-trained LSTM autoencoder neural network, and a feed-forward neural network. This architectural design was motivated by deep learning principles aimed at addressing the specific challenges posed by the NBI dataset.

To begin with, the decision to segregate the sequential and tabular features confers computational advantages over amalgamating them. Moreover, it enables us to harness the benefits of LSTM network for the sequential features while keeping the non-sequential nature of tabular features intact. This approach was chosen because incorporating such non-sequential variables into an LSTM model could lead to an unnecessary increase in complexity without significantly contributing useful information or capitalizing on the LSTM's sequential design.

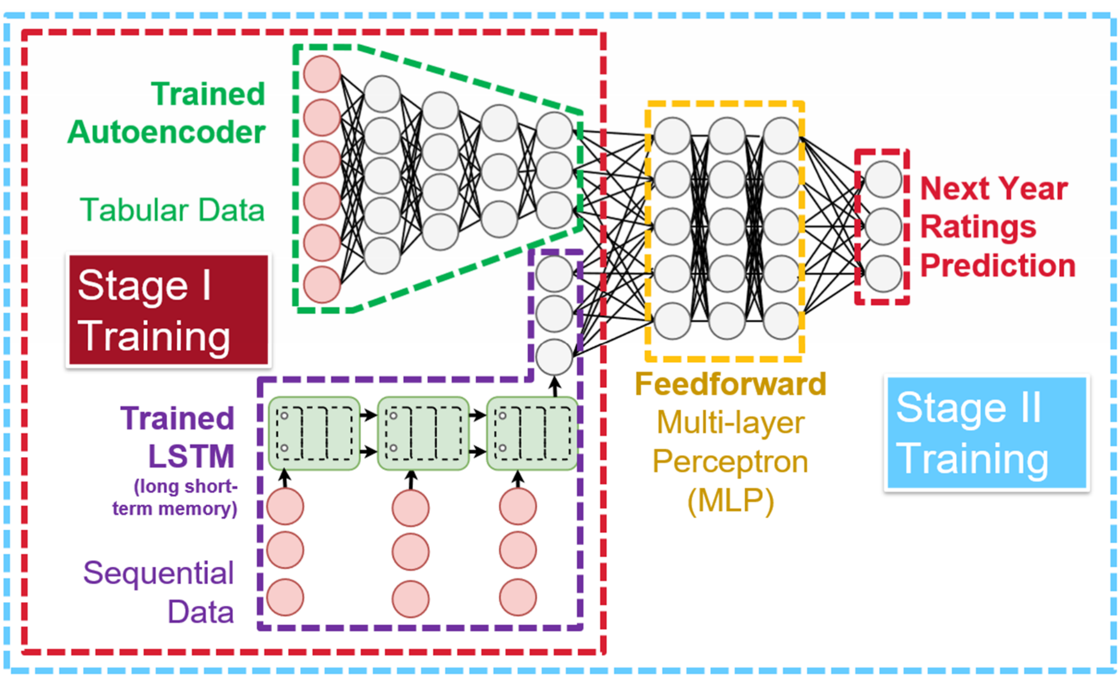


Figure 13 Schematic Architecture of Proposed Deep Neural Network

The decision to incorporate pre-trained components into the final model was influenced by the principles of transfer learning in deep learning. Transfer learning involves using pre-trained models as a foundation for building more specialized models. The rationale behind this approach lies in the fact that pre-trained models have already captured relevant patterns from the data, making them adept at applying their knowledge to other tasks. In the context of our NBI dataset bridge prediction problem, we leverage transfer learning by training unsupervised autoencoder models on the data. This pre-training phase acts as a preparatory step, allowing the network to better handle the actual task of inferring future bridge ratings.

3.2 Autoencoder Architecture

Autoencoder architectures find widespread application in tasks such as data compression, denoising, anomaly detection, and dimensionality reduction. The structure of an autoencoder comprises two interconnected networks, with a compressed layer called the latent layer situated in between. The first network compresses the data from its original space into a lower-dimensional representation within the latent layer. The second network, known as the decoder, reconstructs the data by decompressing it back to its original form. The fact that the input and output of the autoencoder are identical makes the learning process unsupervised.

A fundamental aspect of autoencoders is the ability to access the latent space following successful training. This encoded information is usually free of any redundancy that might exist in the original data. It's crucial to recognize that this redundancy isn't always linear or easily apparent. For instance, certain features in the data may exhibit nonlinear correlations with another set of features. As a result, gaining useful knowledge from one set can offer valuable insights into the other set. Remarkably, autoencoders have demonstrated their effectiveness in capturing such nonlinear relationships between data features and generating a well-compressed version in the latent space.

Next, let's explore incomplete autoencoders, which follow a two-step process. Initially, the autoencoder is trained using the data, and then only the encoder part of the network is utilized to transform the data. As previously mentioned, the output of the encoder serves as a compressed representation of the data, encapsulating as much information from the dataset as feasible. This incomplete autoencoder serves as a valuable data processing tool, especially when dealing with linear or nonlinear redundancies within the data.

In the context of the NBI (National Bridge Inventory) dataset, each bridge is associated with a significant amount of tabular data, and handling this data appropriately before using it for rating prediction is of utmost importance. To address this, we considered the application of an incomplete autoencoder. However, before implementing it effectively, several factors require attention. Firstly, it is crucial to acknowledge that not all bridge features are numerical; some tabular features are categorical. To incorporate these categorical features within the autoencoder architecture, we adopted numerical encoding. This process involved converting categorical values into numerical representations and inputting them into the network accordingly. For instance, if a feature can take on one of three categories, such as "A," "B," and "C," these are encoded numerically as 0, 1, and 2, respectively.

While designing the output layer of the autoencoder, we took special consideration of the categorical nature of these features. To accomplish this, we implemented a one-hot encoding scheme. For each of the three categories ("A," "B," and "C"), we created a corresponding perpendicular vector: [1, 0, 0], [0, 1, 0], and [0, 0, 1], respectively. By adopting this input and output strategy, we ensured that the network comprehended the distinctive metrics associated with each input category independently. Notably, whether a feature was categorical or numerical was left for the network to learn on its own. By meticulously handling both numerical and categorical features through numerical encoding and one-hot encoding, respectively, the incomplete autoencoder can proficiently learn patterns and relationships in the tabular data of the bridges. This heightened understanding of the data's intricate characteristics significantly enhances the accuracy and usefulness of the rating prediction for each bridge in the NBI dataset.

3.3 LSTM Autoencoder Architecture

LSTM represents an advancement over basic recurrent neural networks (RNNs) in addressing the challenges of vanishing or exploding gradients, enabling it to excel in capturing long-term dependencies. This improvement is achieved through memory gates that guide the LSTM cell on what to update or remember. The versatility of the LSTM architecture is evident as it has been effectively applied to various tasks involving both structured and unstructured data.

Recent research by *Liu and El-Gohary 2022* demonstrates that recurrent neural networks perform well on structured NBI data. However, the decision not to use the LSTM architecture for the NBI dataset was based on the belief that short-term dependencies were more prevalent than long-term ones. To capitalize on computational efficiency, alternative RNN architectures were favored. Nonetheless, our proposed method leverages computational efficiency by segregating tabular and sequential features, allowing us to effectively utilize the LSTM architecture without encountering any adverse computational issues.

In our approach, we utilized a pre-trained LSTM autoencoder architecture before utilizing the LSTM encoder to predict the bridge ratings. Similar to the undercomplete autoencoder, the LSTM autoencoder reduces the dimensionality of the input time-based vector, creating an embedding that encompasses all the essential temporal information required for vector reconstruction.

3.4 Two-stage Training

Figure 13 depicts the proposed final architecture, which comprises three main components: the encoder part of the pre-trained undercomplete autoencoder, the encoder part of the pre-trained LSTM autoencoder, and a feedforward neural network. The two latent vectors generated by the autoencoders serve as inputs to the feedforward neural network, producing a probability distribution for next year's ratings. Notably, the final architecture illustrates the network's division into two training stages. In the first stage, the focus lies on training the unsupervised autoencoder networks. In the second stage, the models from stage one are combined into a final model, which is then trained on the bridge rating prediction task. Both stages involve hyperparameter tuning to achieve satisfactory results before incorporating the encoder models into the full model.

Two individually trained models are used to construct the full model. The first model is the Undercomplete Autoencoder, taking 84 tabular features as input. The second model is the LSTM autoencoder, using the historical data of the 12 sequential features as input. Subsequently, the encoder portions of these models are separated, and their learned latent spaces are fed into a feedforward neural network, which provides the desired output of the 3 condition rating features for prediction. It is important to note that within the 12 sequential features used in the LSTM encoder model, the historical data for the 3 condition rating features is also included.

3.5 Design and Tuning of the Neural Networks

3.5.1 The Hyperparameters and Tuning

Once the basic framework for a neural network is selected, it is necessary to design the specific parameters that make up the network. As shown in Figure 14, these parameters include the number of layers, activation functions, loss functions, amongst others. The design process of neural networks is an iterative, although engineering intuition and rule of thumb will help guide the experimental search. Having a deep understanding of what every tunable hyperparameter does will help make decisions and troubleshoot issues during the design process of the network.

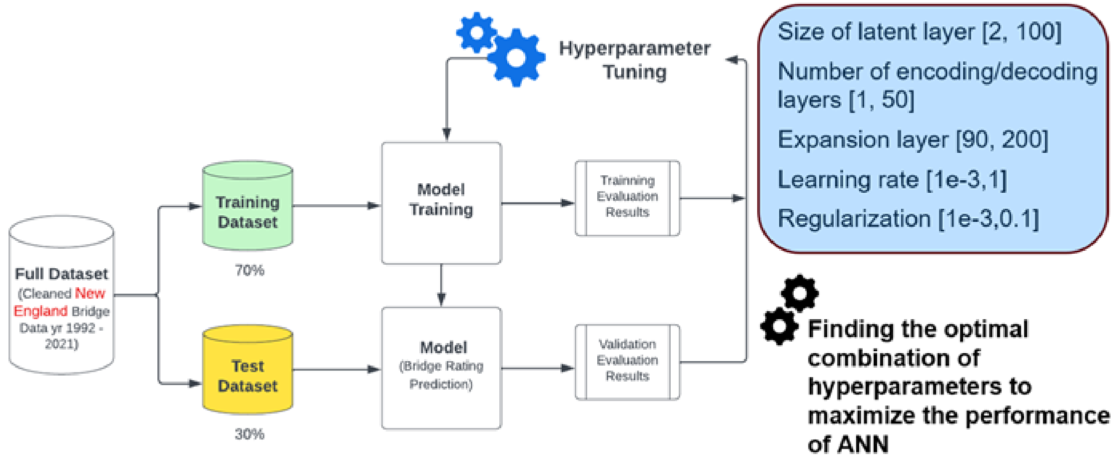


Figure 14 Stage I Training and Testing

The hyperparameters for a network sometimes change depending on the architecture however, many hyperparameters are common across different architectures. Some hyperparameters describe the size of the network, like the number of nodes in each layer and the number of layers. Other hyperparameters affect the training process, like the loss function, learning rate, regularization, etc. The majority of these hyperparameters need to be tuned through experimentation, although some may be chosen based on common industry practice, for example, the activation function at each node was chosen to be ReLu (with the exception of the output layer). ReLu has been shown in practice to provide comparable results to other activation functions while providing a computational advantage on big networks.

Hyperparameter tuning is a crucial step in neural network model training, and it can make a huge difference in your final results. One common strategy for hyperparameter tuning is grid search, this process involves searching through a predefined linear range of values for a general trend that allows for a refined search within the hyperparameter space. Another strategy is random search, which involves setting up a search space and randomly selecting trial points. Random search is more efficient than grid search when there are many hyperparameters to be tuned at once.

Table 7 below shows the tunable hyperparameters for each of the network architectures. The green shade represents hyperparameters that must be tuned for that given architecture, while a red shade means that this hyperparameter does not apply to the architecture. As seen in the table, some hyperparameters are common between the different architectures while others are not.

Table 7 Tuneable Hyperparameters for Each Network Architecture

	Autoencoder	LSTM	Feedforward MLP
Number of latent layer nodes			
Number of encoder/decoder layers			
Learning rate			
Regularization			
Loss function			
Nodes on each layer			
Number of layers			
Activation function for each node			
Batch normalization			

The tuning of most hyperparameters, for example, the number of latent layer nodes, was done using grid search. By defining a search space based on judgement, and then training different models where every hyperparameter is equal except for the one being tuned. All of the models are evaluated based on their mean absolute error loss (MAE), and the optimal setting is chosen to proceed with further tuning of other hyperparameters.

3.5.2 Autoencoder Training

Figure 15 is a proposed architecture for the autoencoder which has a ResNet backbone. Figure 16 shows a plot of the mean absolute error loss for different models with a varying number of latent layer nodes and while all other hyperparameters are constant, which is said Tuning Experiment 1. It is seen that the MAE decreases as the number of latent nodes increases however, one must not simply choose the minimum loss value instead, we choose the value at the elbow point of the graph. This is the optimal point where the return given by increasing the number of nodes is not worth the cost of a larger network.

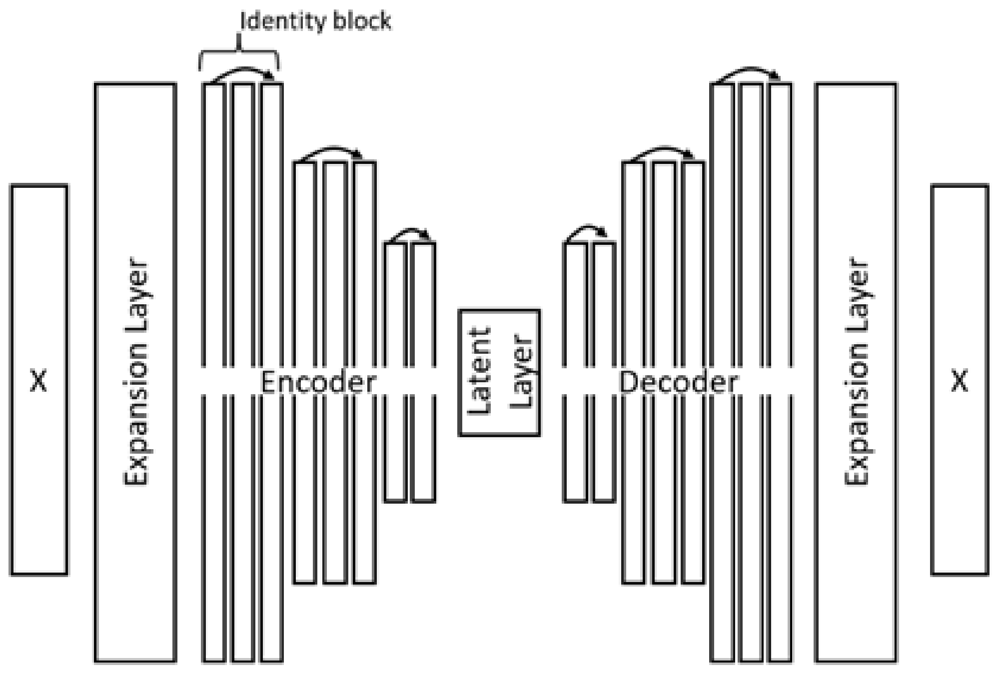


Figure 15 Autoencoder Architecture with ResNet BackBone

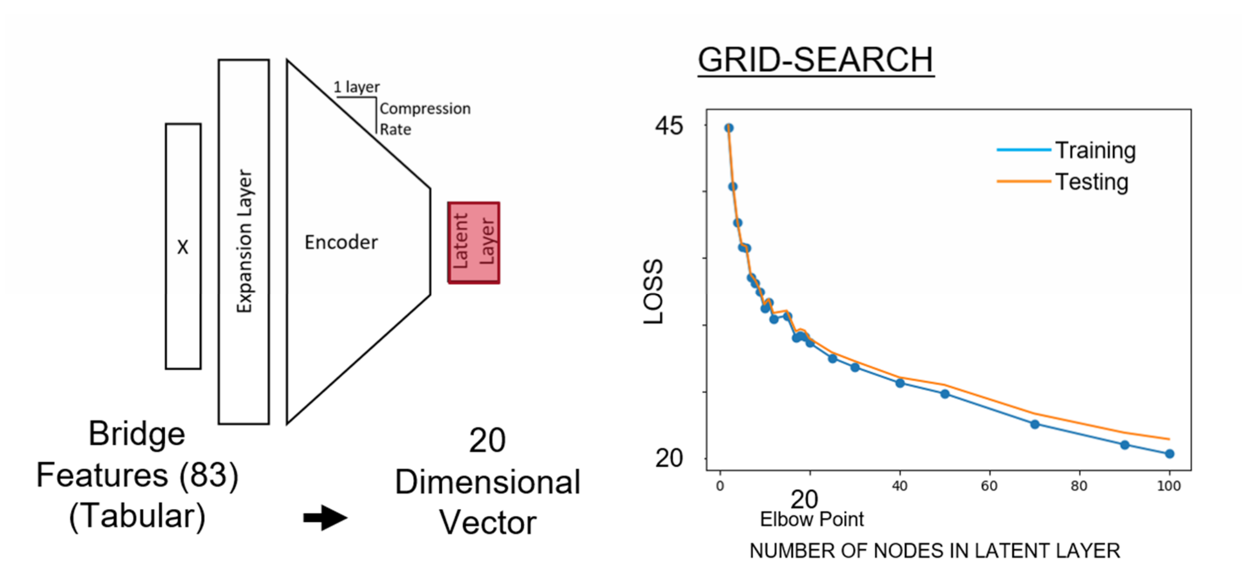


Figure 16 Autoencoder Model Tuning, Experiment 1 Bottleneck Size

The tradeoff with the number of latent layer nodes is that by increasing its size, we allow more noise to pass from the encoder to the decoder, making the reconstruction task much easier. While reducing the dimensionality to a smaller dimension makes the task harder, this will inevitably increase the loss. Similar tradeoffs are seen with other hyperparameters, and this is the challenge of hyperparameter tuning.

Figures 17 - 20 show the results of the tuning of the other key network parameters in addition to later layer nodes, such as the encoder layer, expansion layer, depth of identity blocks and the learning parameters such as learning rate, regularization and epochs. The optimal values of the hyperparameters are provided in Figure 21.

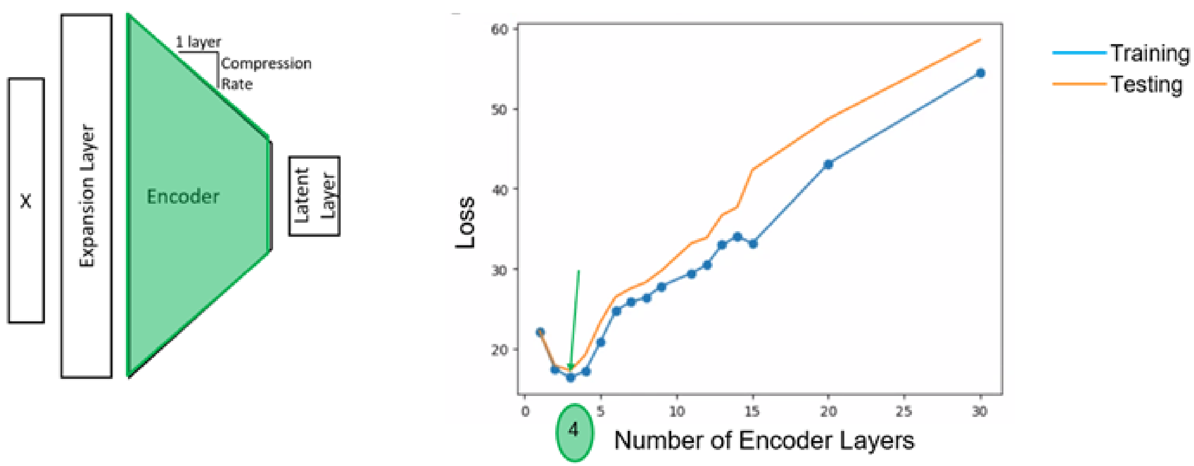


Figure 17 Autoencoder Model Tuning, Experiment 2 Number of Encoder Layer

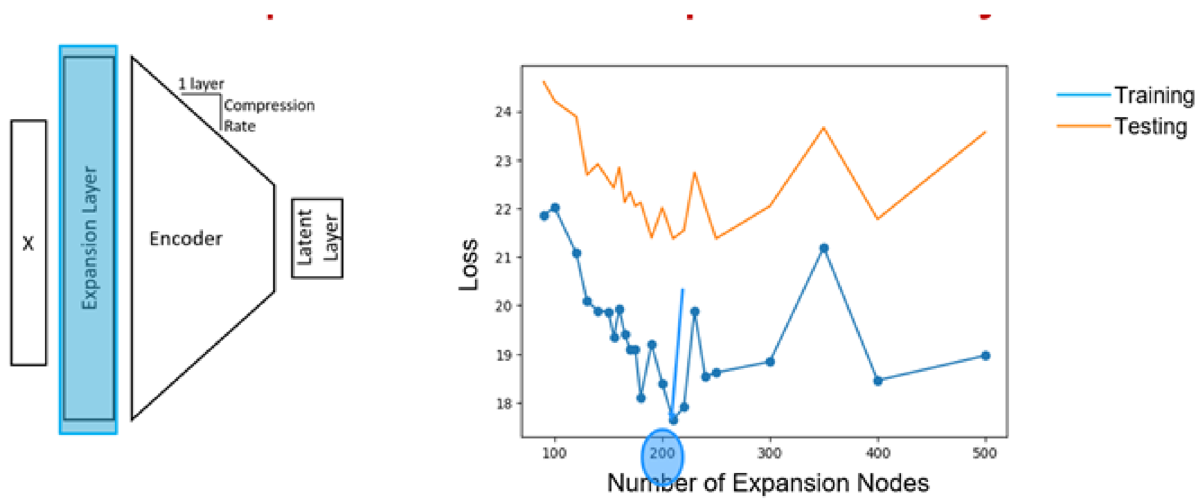


Figure 18 Autoencoder Model Tuning, Experiment 3 Expansion Layer

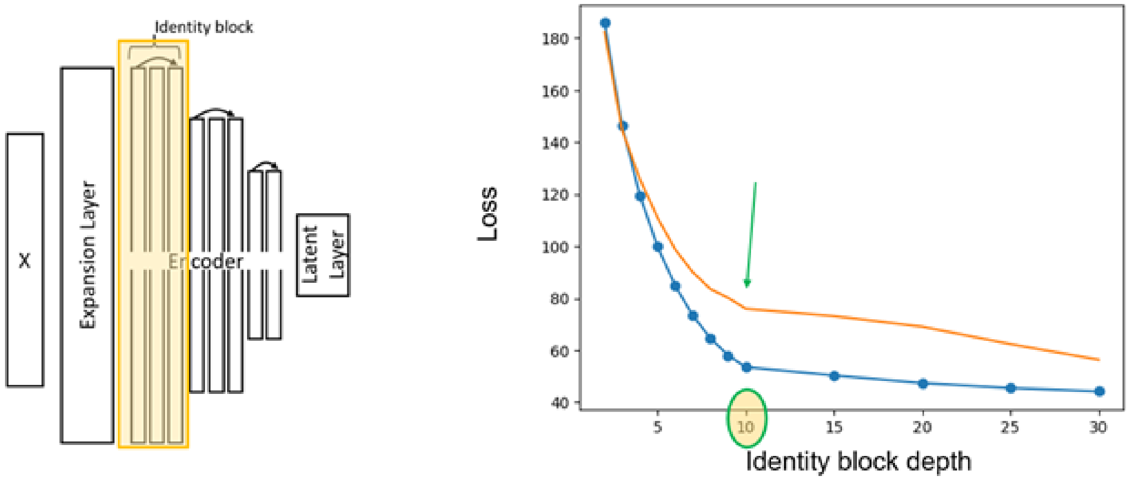


Figure 19 Autoencoder Model Training, Experiment 4 Depth of Identity Block

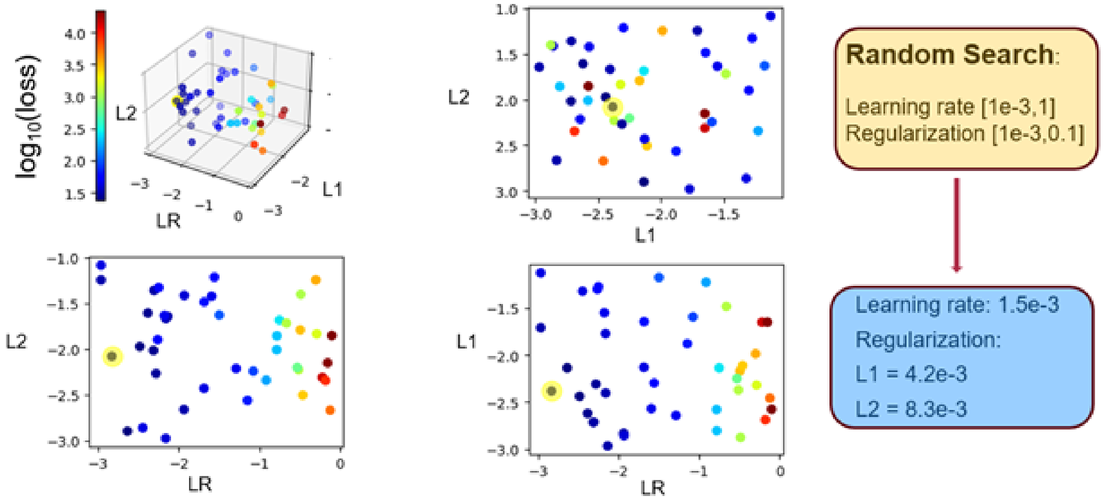


Figure 20 Autoencoder Model Tuning, Experiment 5 Learning Rate and Regularization

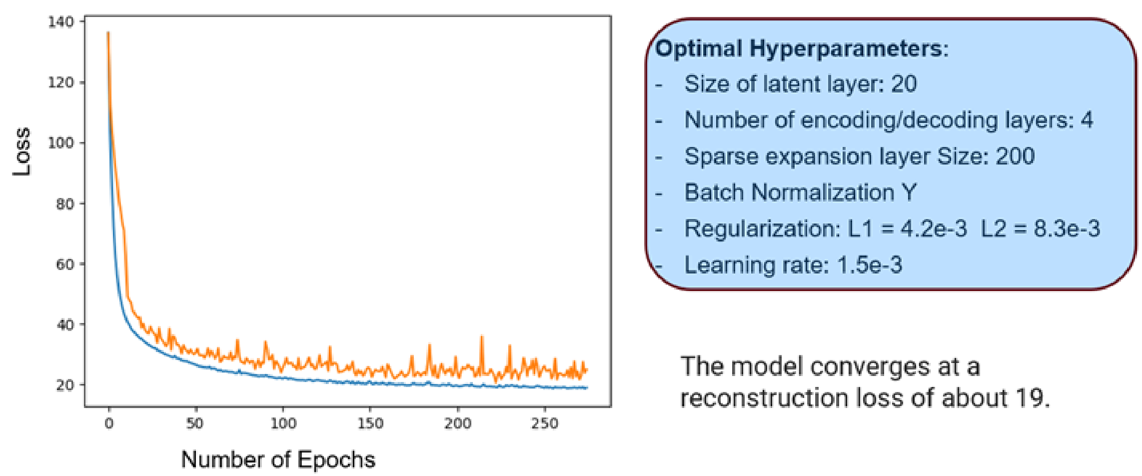
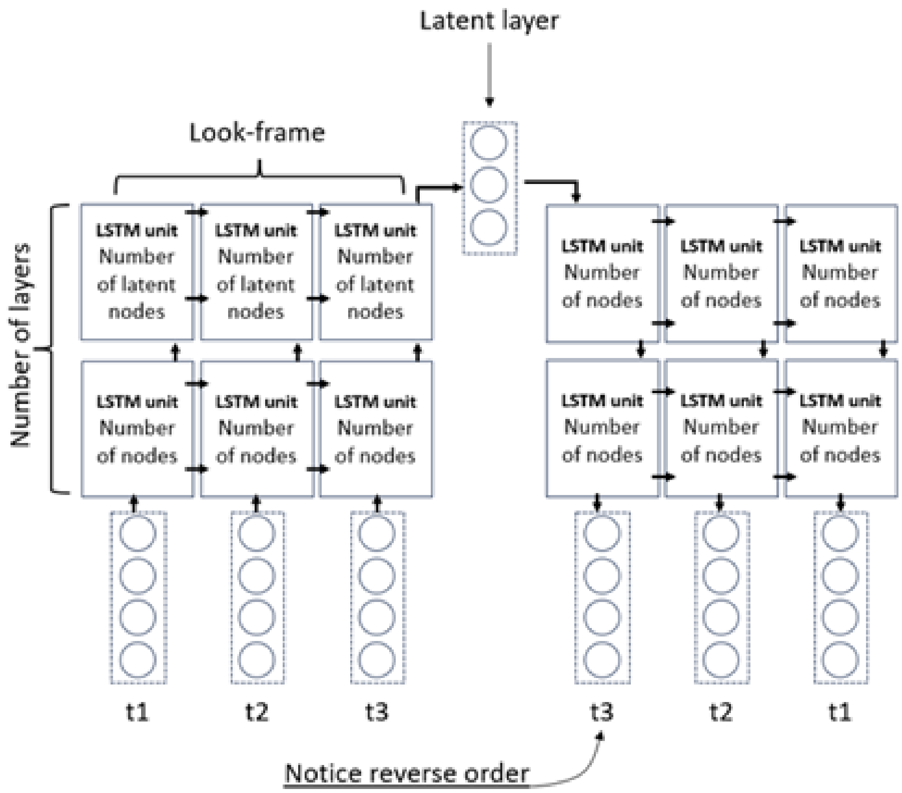


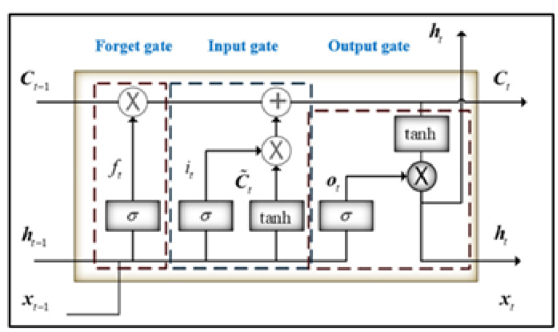
Figure 21 Autoencoder Model Training, Experiment 5 Number of Epochs

3.5.3 LSTM Model Training

We employed LSTM autoencoder to compress the sequential features into latent space using the architecture shown in Figure 22. With this architecture, using random search we trained 200 models with respect to number of layers, number of nodes, number of latent nodes and the size of Look-frame. The tuning results are provided in Figure 23



(a) LSTM architecture



(b) One LSTM Node

Figure 22 LSTM Autoencoder for Sequential Data

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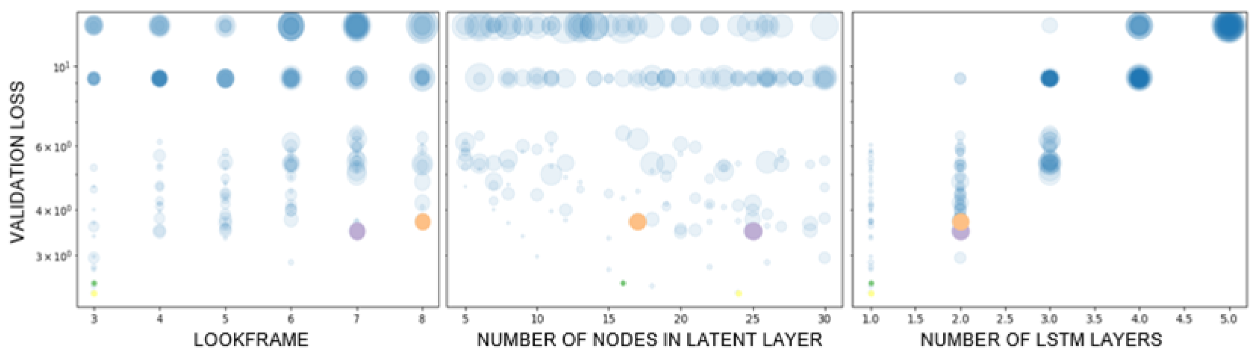
In the training, we applied a LOSS normalized over the size of Look-frame, expressed below:

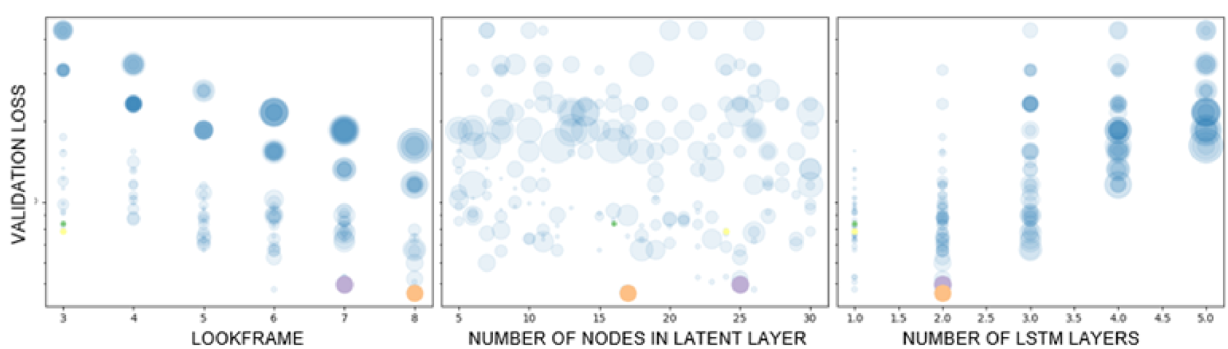
$$= \frac{\qquad}{\qquad}$$

LOSS normalization is a technique commonly used in language models to incentivize models to predict longer sequences.

In the end a total of 4 models with different combinations of Look-frame, number of nodes in latent layers, and number of LSTM layers were chosen to pass to the next stage of training. In addition, the results have also shown a Look-frame of 8 years could generate promising predictions.



(a) LSTM Hyperparameter Training Results



(b) Training Results with Adding Length Normalization

Figure 23 LSTM Hyperparameter Training Results

3.5.4 Stage II Training

The focus of Stage II training was on the Multi-layer Perceptron (MLP) model, illustrated in Figure 24. We employed a random search strategy to train 150 models, adjusting parameters such as the number of nodes and layers of the MLP relative to the Long Short-Term Memory (LSTM) model. The results of these training sessions are depicted in Figure 25.

At the conclusion of Stage II training, we successfully developed an AI deep learning model for bridge rating prediction, as shown in Figure 26. The final model architecture comprises 37 nodes and 4 layers. The outputs of this model are the rating conditions for the deck, superstructure, and substructure.

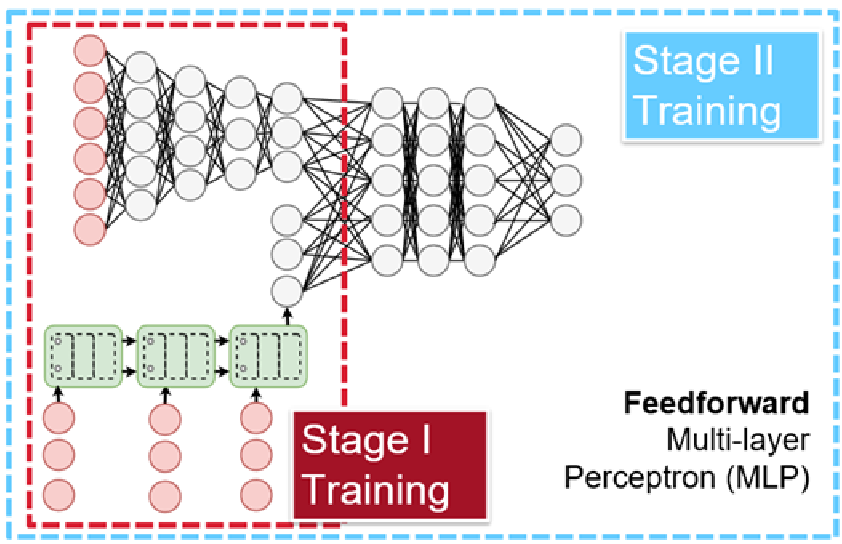


Figure 24 Stage II Training, Feedforward Multi-layer Perceptron

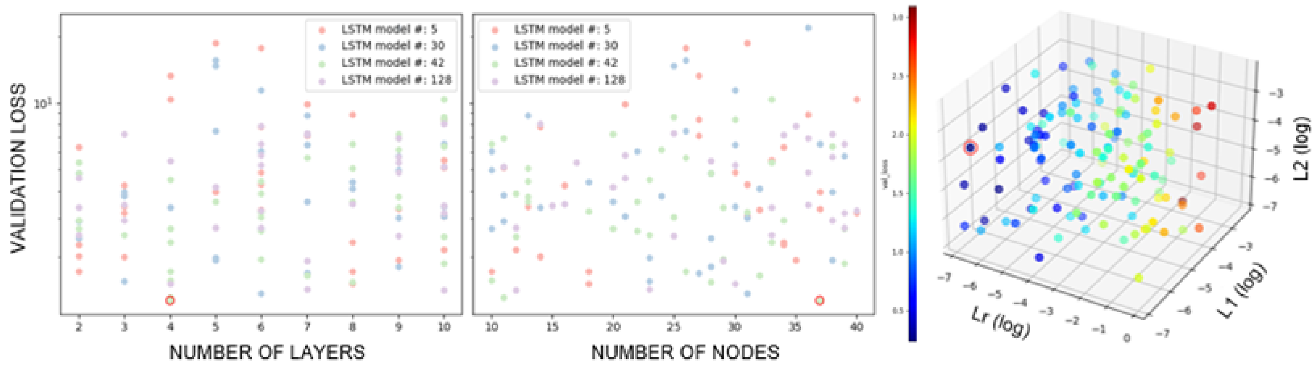


Figure 25 MLP Hyperparameter Tuning Results

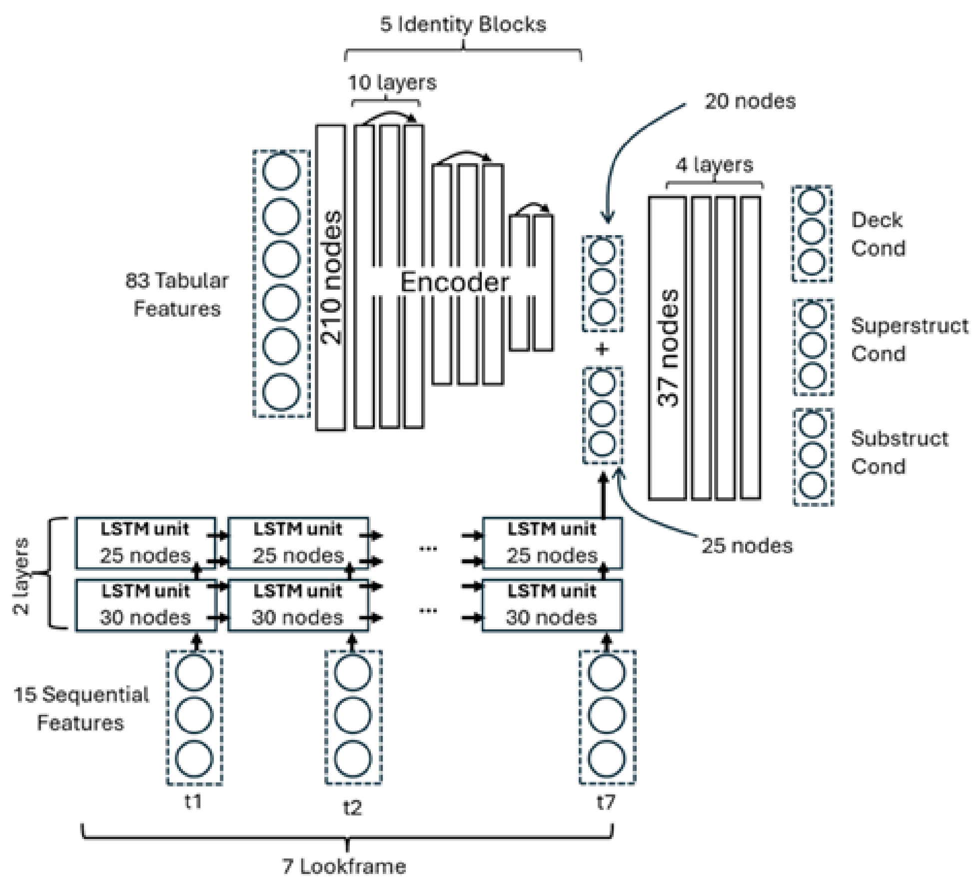
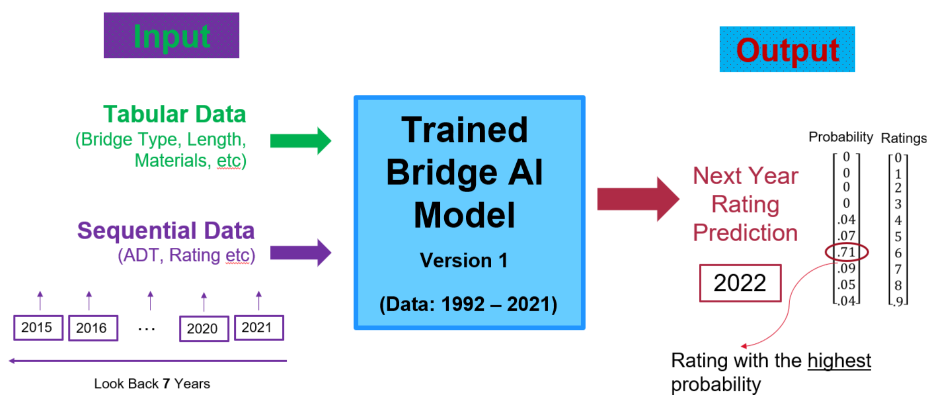


Figure 26 Trained Bridge Rating Prediction Model by AI Deep Learning

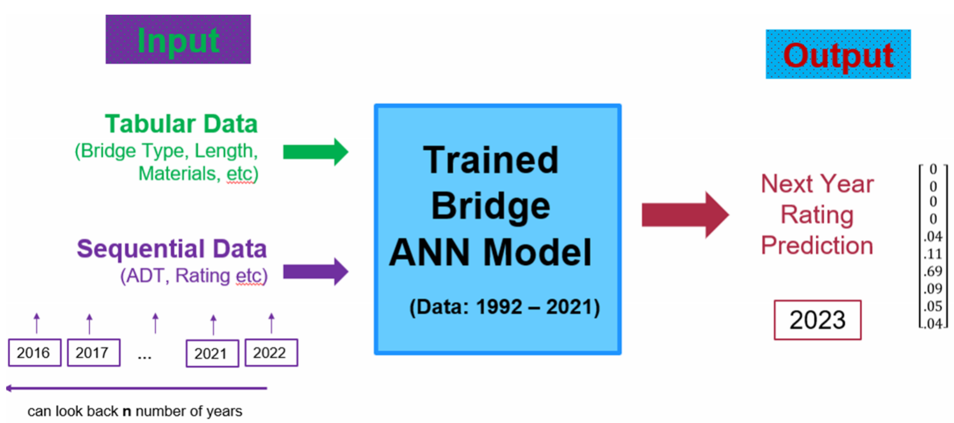
CHAPTER 4 BRIDGE RATING PREDICTION MODEL AND IMPLEMENTATION

4.1 Concept of the Bridge Rating Prediction Model

Figure 27 illustrates the application of the Training Bridge AI model (Figure 26) for predicting bridge ratings for the upcoming year. For the 2022 rating prediction, the model uses a look-back period of 7 years, spanning from 2015 to 2021. Both tabular and sequential data are fed into the Trained Bridge AI model, which outputs the ratings for the following year. The model then selects the rating with the highest probability as the prediction outcome. In the example shown, the newly predicted rating for 2022 is 6, with a probability of 71%. To predict the results for 2023, the rating of 2022 is incorporated into the new look-back period, now spanning from 2016 to 2022.



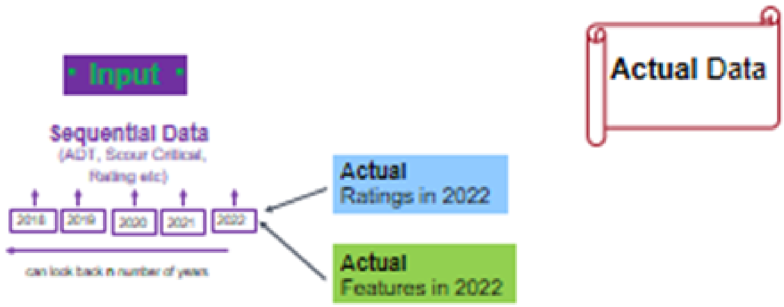
(a) Prediction for Year 2022



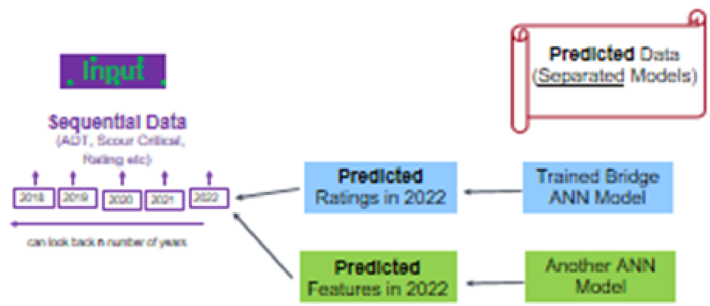
(b) Prediction for Year 2023

Figure 27 Application of the Bridge Rating Prediction Model

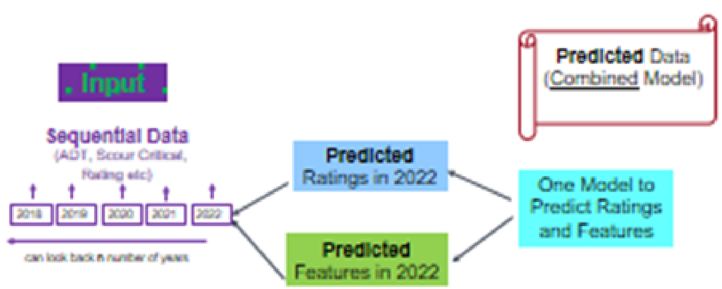
When applying the model to predict the bridge rating for 2023, there are several approaches to handle the 2022 rating data. As shown in Figure 28, we can adopt one of the following methods:



(a) Actual Rating and Actual Features in 2022



(b) Predicted Rating and Predicted Features in 2022 with Separated Models



(c) Predicted Rating and Predicted Features in 2022 with One Model

Figure 28 Three Different Ways to Apply the Trained Model

1. **Actual Rating and Features for 2022**: Utilize the actual rating and features from 2022, if available, as depicted in Figure 28(a).
2. **Separately Predicted Rating and Features for 2022**: Employ ratings and features predicted independently for 2022, as shown in Figure 28(b).
3. **Integrated Model for 2022**: Apply a single model to predict both the rating and features for 2022, illustrated in Figure 28(c).

Each approach offers different insights and implications for forecasting the 2023 bridge rating."

4.2 Final Improvement on Bridge Rating Prediction Model

The initial application of the trained model produced results where bridge ratings showed minimal or no change, which proved unacceptable. Upon reviewing the historical data from 1992 to 2021, we observed that very few bridges had ratings dropping to 4 or below, as illustrated in Figure 29.

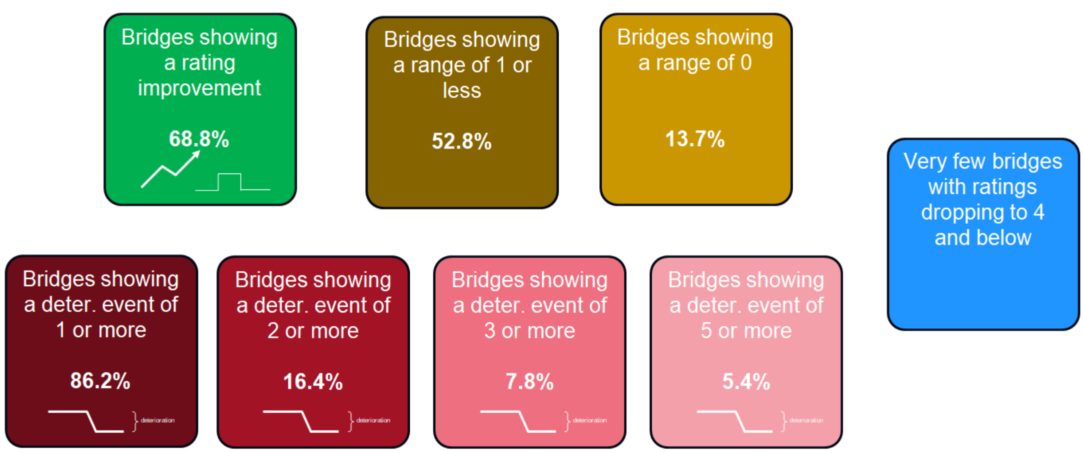


Figure 29 Analysis of Historical Bridge Ratings

This trend indicates that when bridge ratings fall to a condition rating of 4, they are typically subjected to repair or rehabilitation. Since these interventions are human decisions rather than part of the natural deterioration process, we considered two key solutions to enhance the prediction model:

a) Data Filtering with Sliding Window:

We applied a sliding window filter to remove data points where the bridge rating showed an upward trend, as shown in Figure 30. For instance, between 1998 and 2005, the rating increased from 5 to 8 between 2004 and 2005. We removed this upward trending datato refine our model. Please note that the only removed bridge data was due to the upward trend.

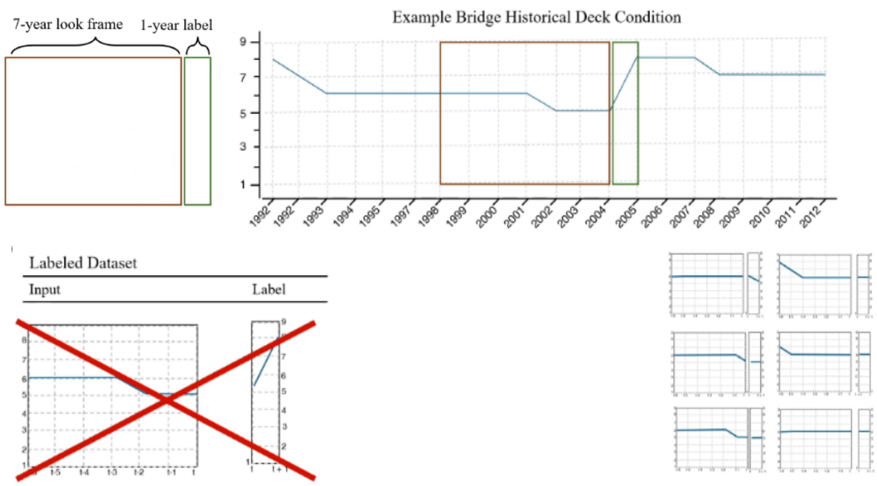


Figure 30 Clean the Data With 8-Year Window

b) Addition of Output Nodes**:**

We enhanced the neural network by adding three output nodes to capture changes in deck, superstructure, and substructure ratings. This modification is designed to improve sensitivity to rating changes and ensure that these variations are accurately reflected in the deep learning. The updated model, as illustrated in Figure 31, incorporates these additional nodes to better capture changes during iterations.

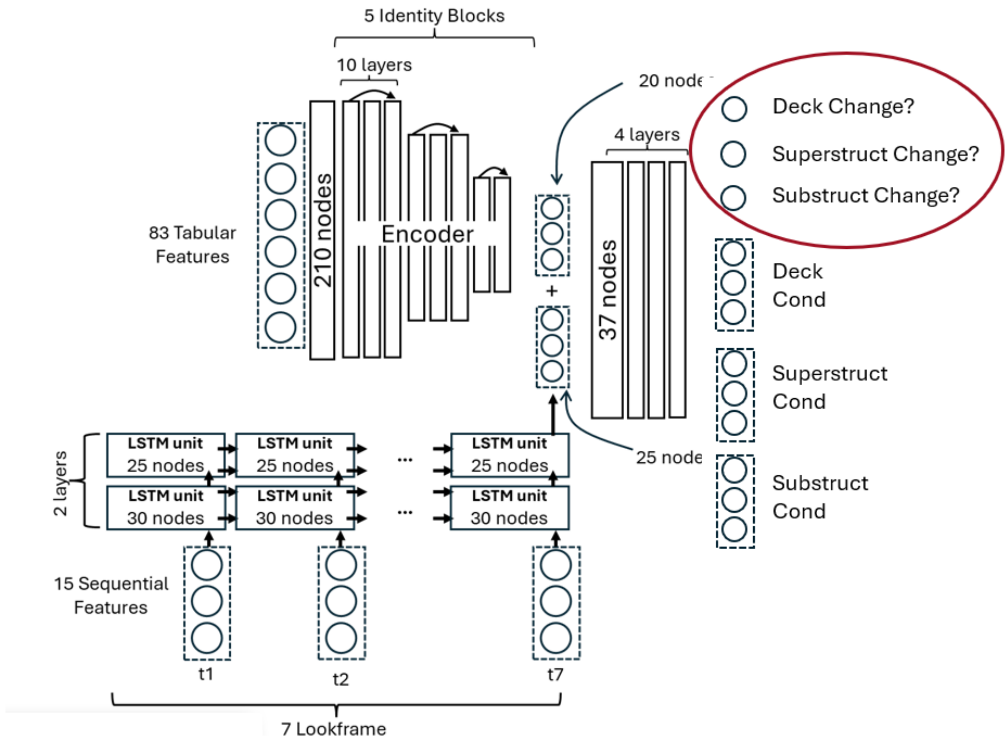


Figure 31 The Final Bridge Rating Prediction Model using AI

4.3 Model Accuracy

Accuracy is defined as the ratio of correctly predicted ratings for the deck, superstructure, and substructure to the total number of predicted samples. With the recent improvements (Figure 31), we achieved a prediction accuracy of 94% for both the superstructure and substructure ratings, and 93% for the deck rating.

$$=$$

4.4 Develop a Website for Model Implementation

Although website or app development was not part of the project contract, we recognized its potential value for utilizing the developed bridge rating prediction model. Below are some key functions of the website we have developed:

- Main/Login page
- Search (integrated with Google Maps)
- Bridge Characteristics
- Individual Bridge Rating Prediction Results

The login page (Figure 32) restricts access to authorized users only and provides a brief summary of the project.

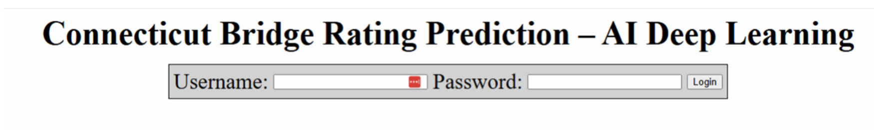


Figure 32 Login Page

Once logged in, users can search by any category that identifies a bridge (Figure 33). If multiple bridges match the search criteria, users can select from a drop-down list containing all possible bridges.

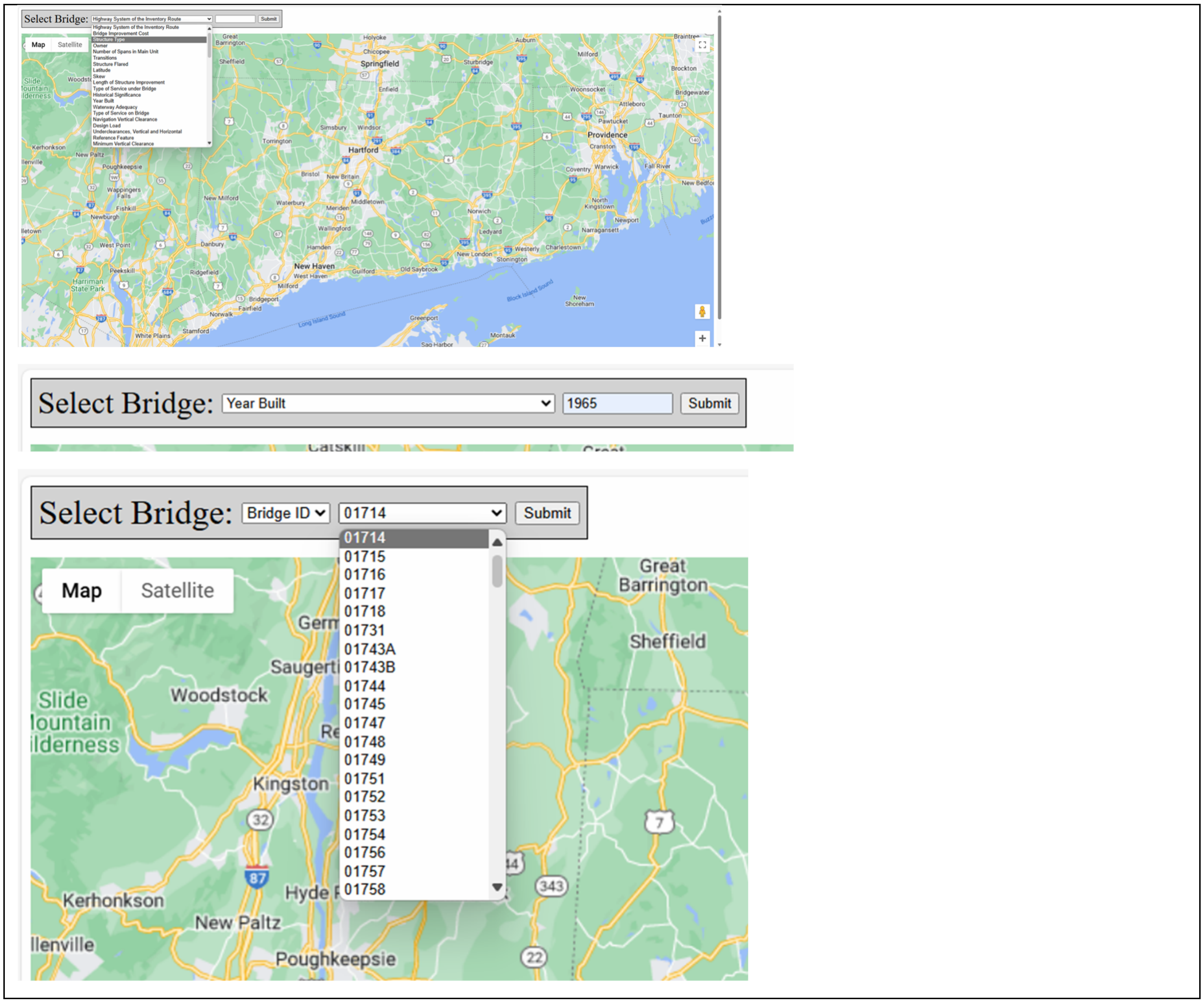


Figure 33 Search by Bridge ID, or Location Information

Upon selecting a bridge, users will be presented with a map view and street view of the bridge's location. This view includes its identifying characteristics (tabular data), historical data, and predicted statistics (sequential data), as shown in Figure 34. The tabular data includes bridge ID, year built, lanes on, lanes in, max span, bridge length, and various bridge characteristics. Predicted results for deck ratings, superstructure ratings, and substructure ratings are also displayed. To provide users with a comprehensive understanding of the bridge deterioration process, both historical and predicted conditions of the bridges are shown. Additionally, users can view the Probability Distribution of Ratings by selecting Deck, Superstructure, and Substructure, along with the predicted year.

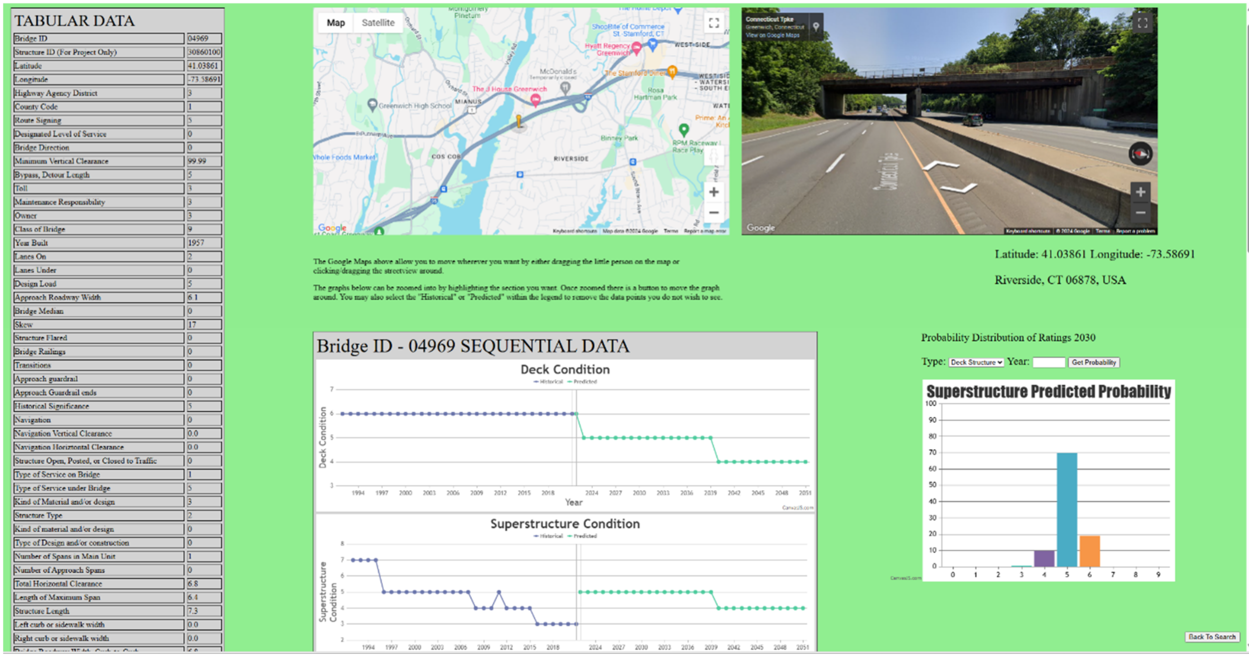


Figure 34 Bridge Rating Prediction Main Page

All graphs are interactive, allowing users to zoom in by highlighting sections and navigating through the zoomed-in view. Users can toggle between predicted and historical data points on a graph by clicking to hide or display each dataset.

The website integrates Google Maps to display the location and visual appearance of selected bridges. It is built using coding languages such as JavaScript, Java, CSS, and HTML, ensuring a seamless user experience. A Google API account is required to use all the map features.

CHAPTER 5 RESULTS ANALYSIS

We applied the final bridge rating prediction model, as shown in Figure 31, to forecast bridge ratings for the next 100 years (2022-2121). While these long-term predictions highlight trends in bridge deterioration, the final project deliverables (Appendix A) include predictions for a more manageable 30-year span for each bridge. The primary results are discussed below, focusing on the deterioration trends for all Connecticut bridges, specific typical bridges, and those identified as high-risk.

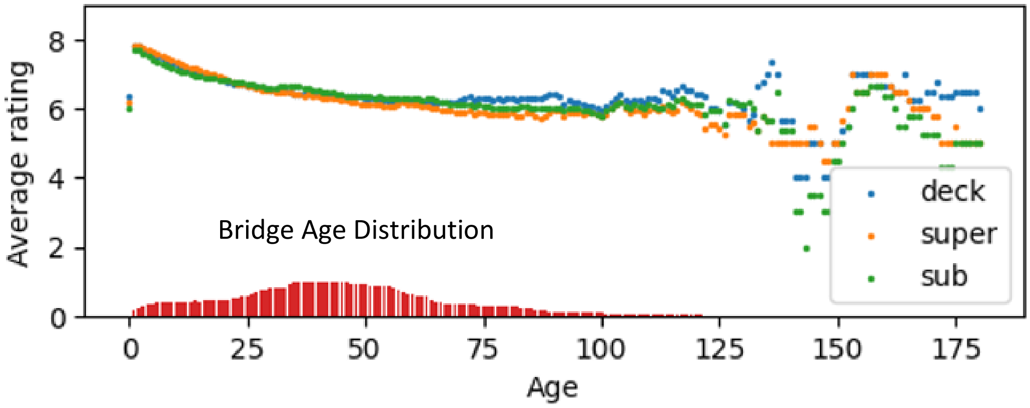
5.1 The Deterioration Trends of All Bridges

5.1.1 Average Rating of All Connecticut Bridges in terms of Ages

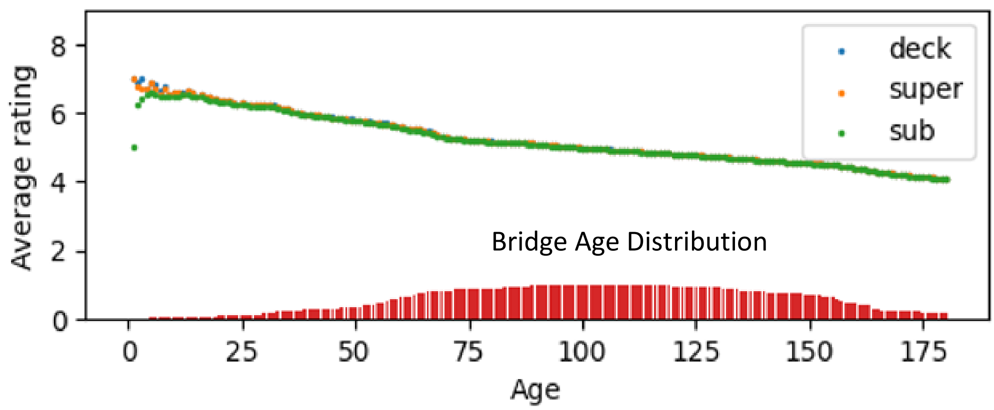
Figure 35 displays the average ratings versus age for all Connecticut bridges, comparing 30 years of historical data with 100 years of predicted ratings for decks, superstructures, and substructures. Key findings include:

- There are no significant differences among deck, superstructure, and substructure ratings.
- Historical data indicates potential improvements in ratings due to rehabilitation, repair, and maintenance.
- The predictions project consistent deterioration trends for decks, superstructures, and substructures.
- The red bar graph illustrates the distribution of bridges across various age groups. Over the past 30 years, Connecticut bridges are mostly between 25-50 years old, considered relatively young. Over the next 100 years, bridge ages will shift rightward on the x-axis, with most bridges aging to 75-110 years.

Please also note for very young bridges, the predictions may not be accurate due to the limited amount of data available for bridges of this age.



(a) 30 Years Historical Data (1992 – 2021)



(b) 100 Years Prediction (2022 – 2121)

Figure 35 Average Ratings of All Connecticut Bridges vs. Ages

Note: Red Bar Graph stands for Distribution of Bridges Across Various Age Groups

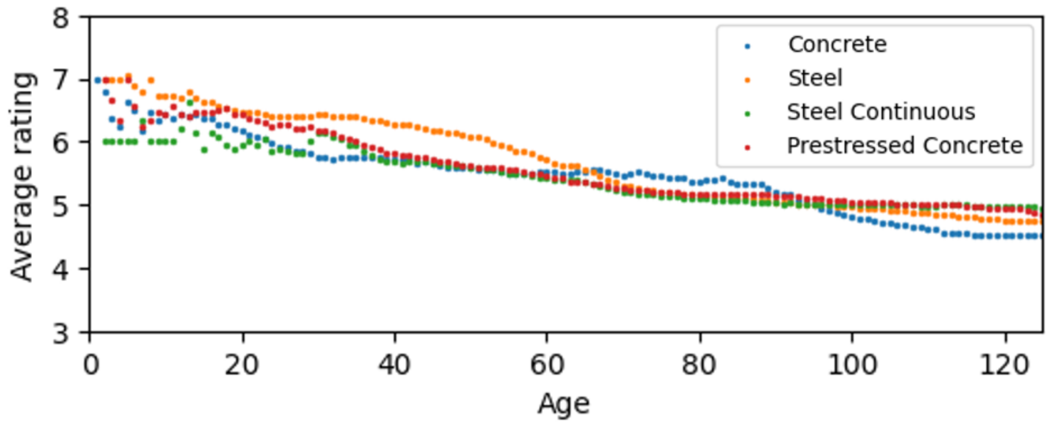
5.1.2 Bridge Rating Predictions vs. Bridge Ages

a) <u>Ratings vs. Bridge Ages with respect to Bridge Materials</u>

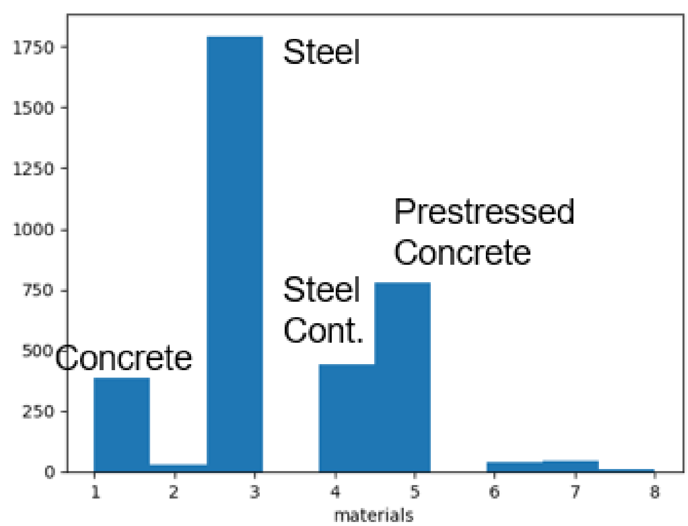
Figure 36 presents the average superstructure rating versus age (2022-2121) with respect to bridge materials. Key observations include:

- Concrete vs. Steel: Concrete bridges generally perform worse than steel bridges. Steel bridges deteriorate more rapidly after 40-50 years.
- At ages 60 to 80, ratings for steel and concrete are similar, but concrete deteriorates faster afterward.

- Prestressed concrete and steel continuous bridges show gradual deterioration without significant drops.
- Deck and substructure ratings show similar trends.
- The blue bar chart shows the distribution of bridges by material, with steel being the most common.



(a) Average Superstructure Rating vs. Age



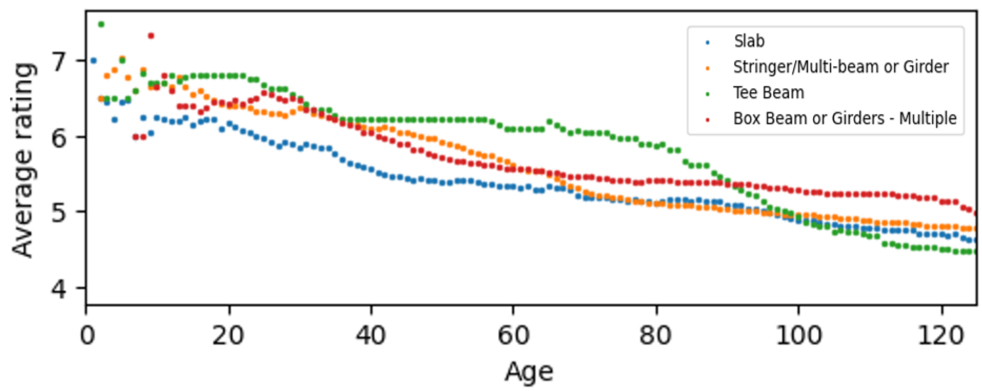
(a) Distribution of Bridges by Materials

Figure 36 Average Superstructure Ratings vs Ages over 2022-2121, with respect to Bridge Materials

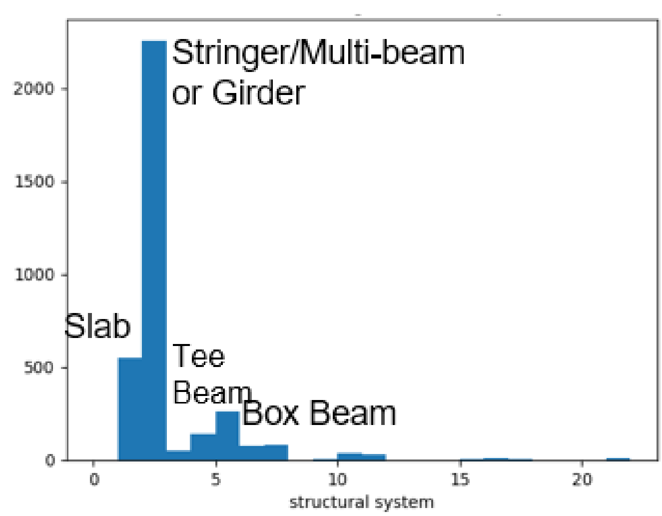
b) Ratings vs. Bridge Ages with respect to Bridge Systems

Figure 37a presents the average substructure ratings versus ages (2022-2121) with respect to bridge systems (Figure 37b). Key observations include:

- Tee beam bridges perform the best but experience rapid rating drops after age 80.
- Stringer or multi-beam bridges deteriorate quickly after age 40.
- Slab and box beam bridges show similar patterns, with slab bridges performing the worst.



(a) Average Superstructure Ratings vs. Ages

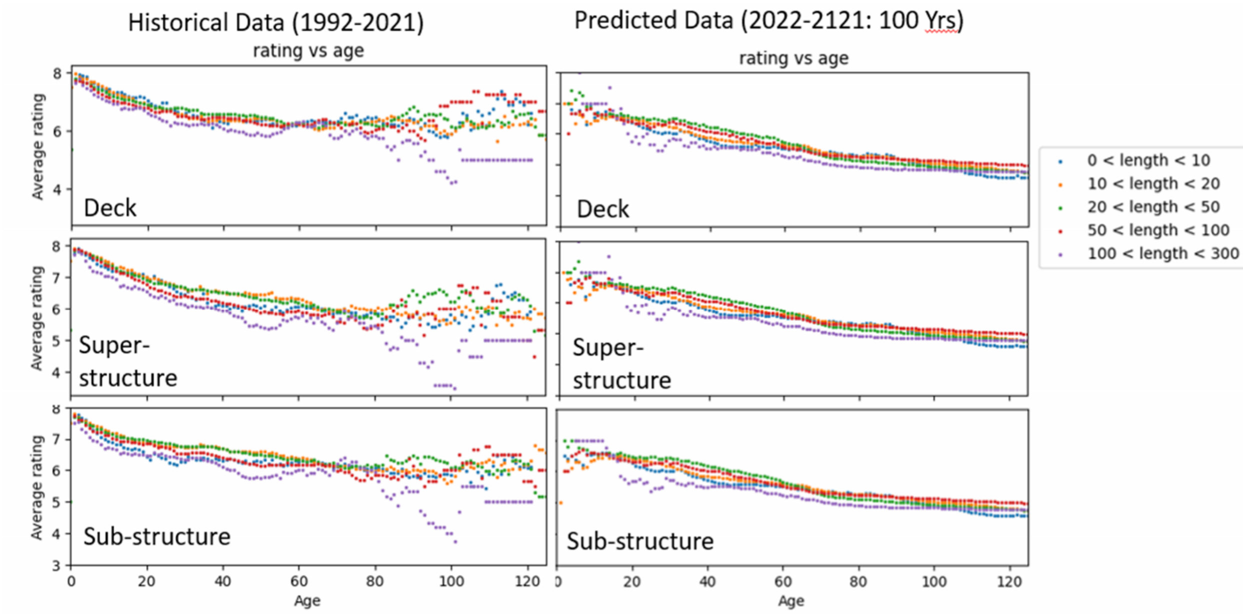


(b) Distribution of Bridges by Structural Systems

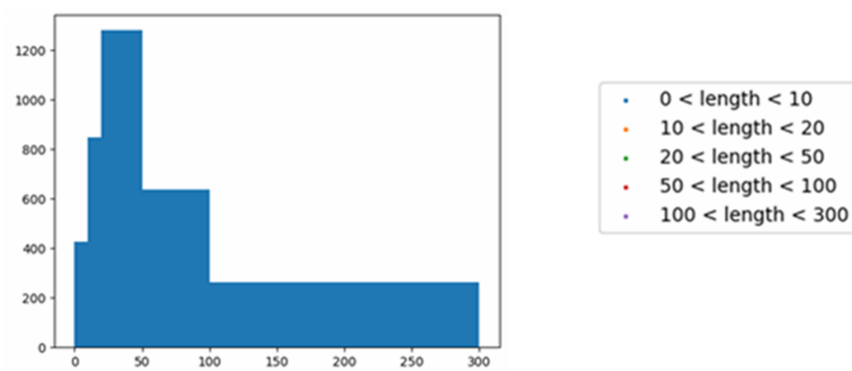
Figure 37 Average Superstructure Ratings vs. Ages over 2022-2121, with respect to Bridge Systems

c) Ratings vs. Bridge Ages with respect to Bridge Spans

Figures 38 presents average historical (1992-2021) and predicted (2022-2121) ratings for various bridge ages with respect to bridge spans.



(a) Historical Rating vs Predicted Rating vs. Ages



(b) Distribution of Bridges by Bridge Spans

Figure 38 Historical vs Predicted Ratings vs Ages, with respect to Bridge Spans

Some key observations of these trends include:

- Historical data trends are similar to predicted trends, though predicted ratings generally decline.
- Historical ratings improve with age due to rehabilitation and repairs.
- Bridges with the longest (100-300 ft) and shortest (0-10 ft) spans perform the worst over time.

d) <u>Ratings vs. Bridge Ages with respect to Annual Daily Traffic (ADT)</u>

As shown in Figure 39, some key observations include:

- Bridges with the highest ADT (100,000-150,000) deteriorate faster, particularly after age 50.

- Bridges with low traffic (5,000-20,000) perform the best.

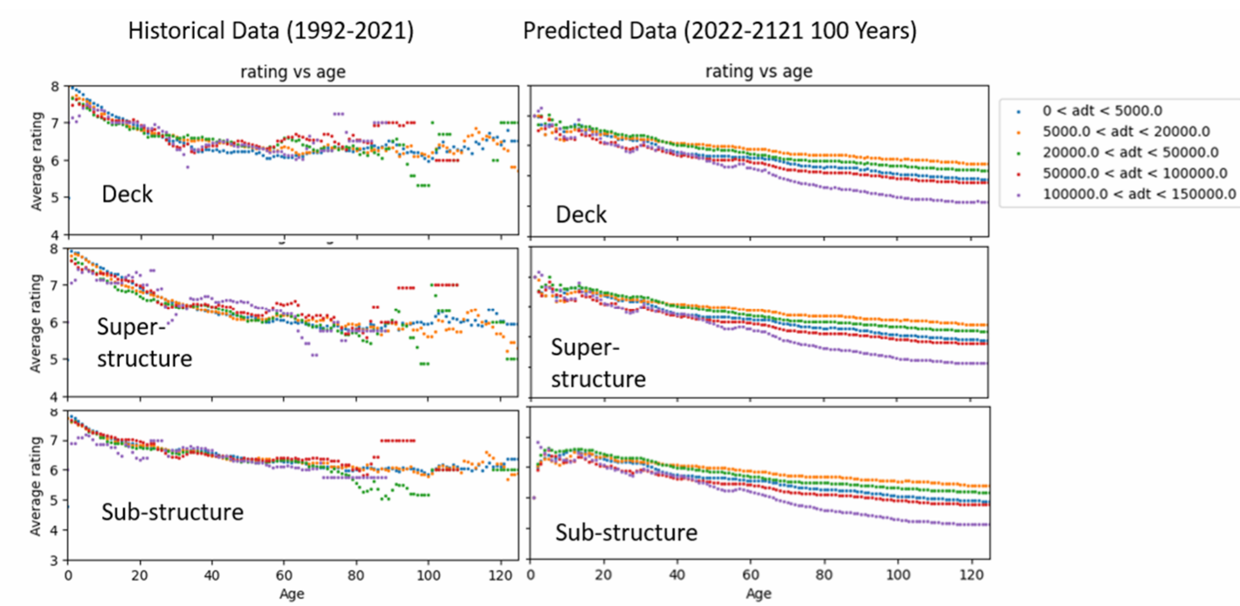


Figure 39 Historical vs Predicted Ratings vs Ages, with respect to ADT

5.1.3 Bridge Ratings vs. Prediction Years

We also studied how bridge ratings change over the prediction years.

a) <u>Ratings vs. Prediction Years with respect to Bridge Materials</u>

As illustrated in Figure 40, concrete bridges exhibit the poorest performance compared to steel and other bridge types. When combined with the performance data of concrete bridges by age (Figure 36), it is evident that the concrete bridges in Connecticut are relatively young.

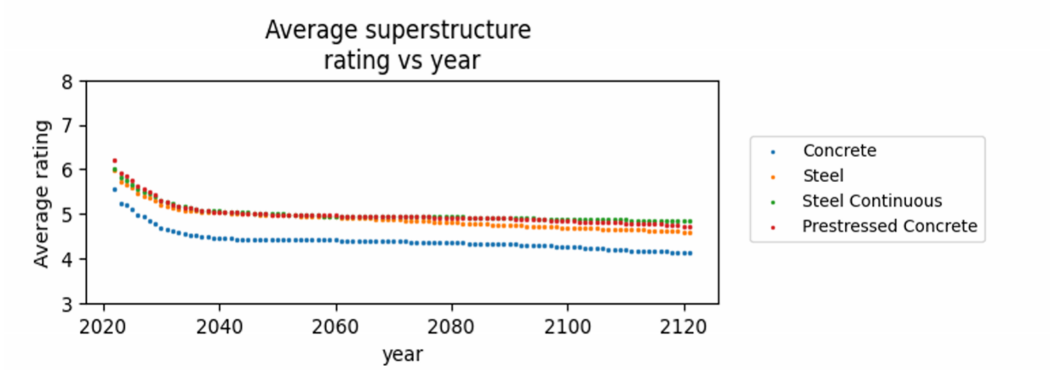
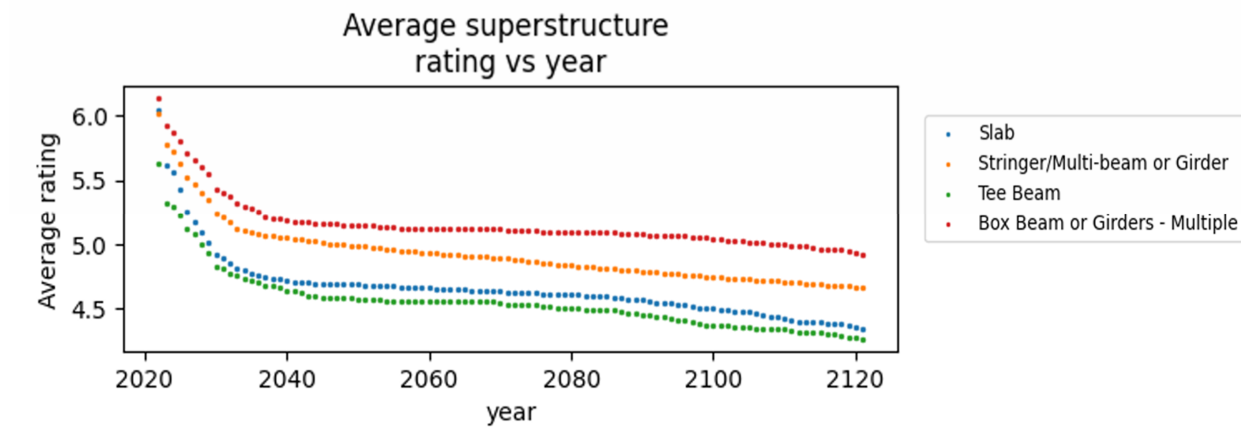


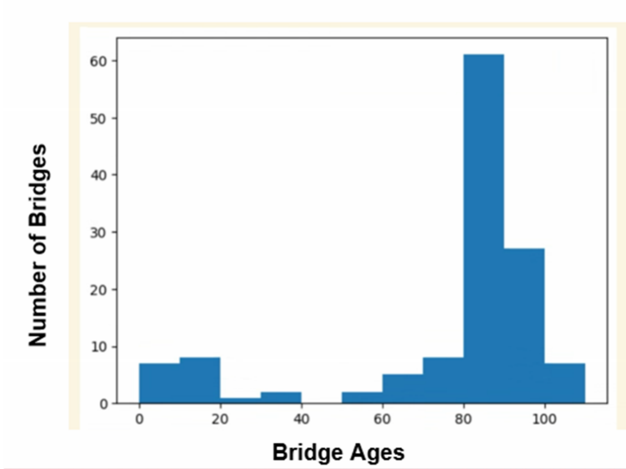
Figure 40 Predicted Rating vs Prediction Years, with respect to Bridge Materials

b) <u>Ratings vs. Prediction Years with respect to Bridge Systems</u>

Over the years, Tee beam bridges have shown the poorest performance compared to other types, while box beam or girder bridges have achieved the highest ratings, as illustrated in Figure 41. Conversely, an analysis of bridge ratings versus age reveals that Tee beam bridges perform the best initially but experience rapid rating declines after reaching 80 years of age. This finding is supported by the distribution data, which indicates that many bridges in Connecticut are over 80 years old.



(a) Predicted Ratings vs. Prediction Years (2022-2121)



(b) Distribution of Tee Beam Bridges by Ages

Figure 41 Predicted Rating vs Prediction Years, with respect to Bridge Systems

c) <u>Ratings vs. Prediction Years with respect to ADT</u>

As depicted in Figure 42, the predictions indicate that bridges carrying the highest ADT (100,000 to 150,000) or the lowest ADT (0 to 5,000) have the lowest ratings. This scenario was not, however, evident in the historical data.

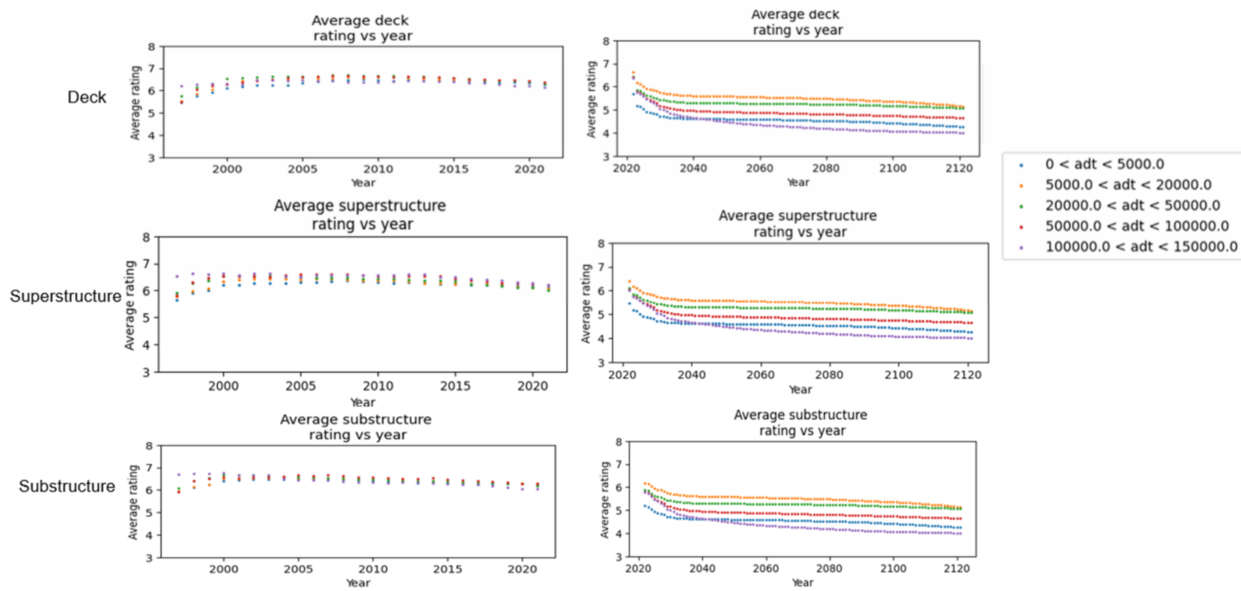


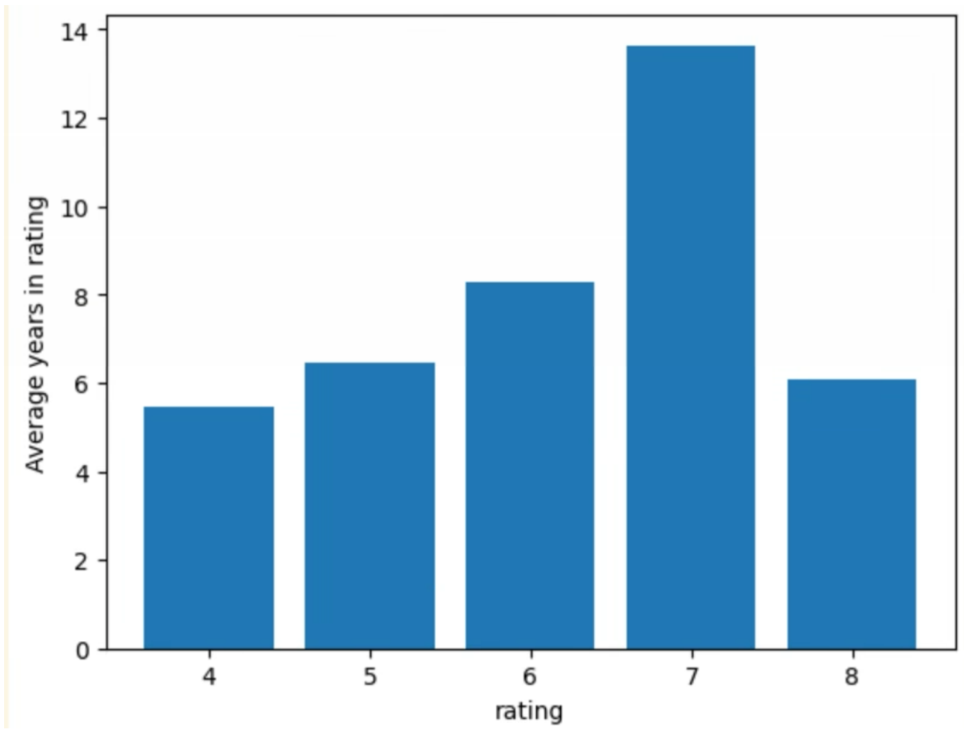
Figure 42 Historical vs Predicted Rating vs Prediction Years, with respect to ADT

5.2 Case Studies on Individual Bridges

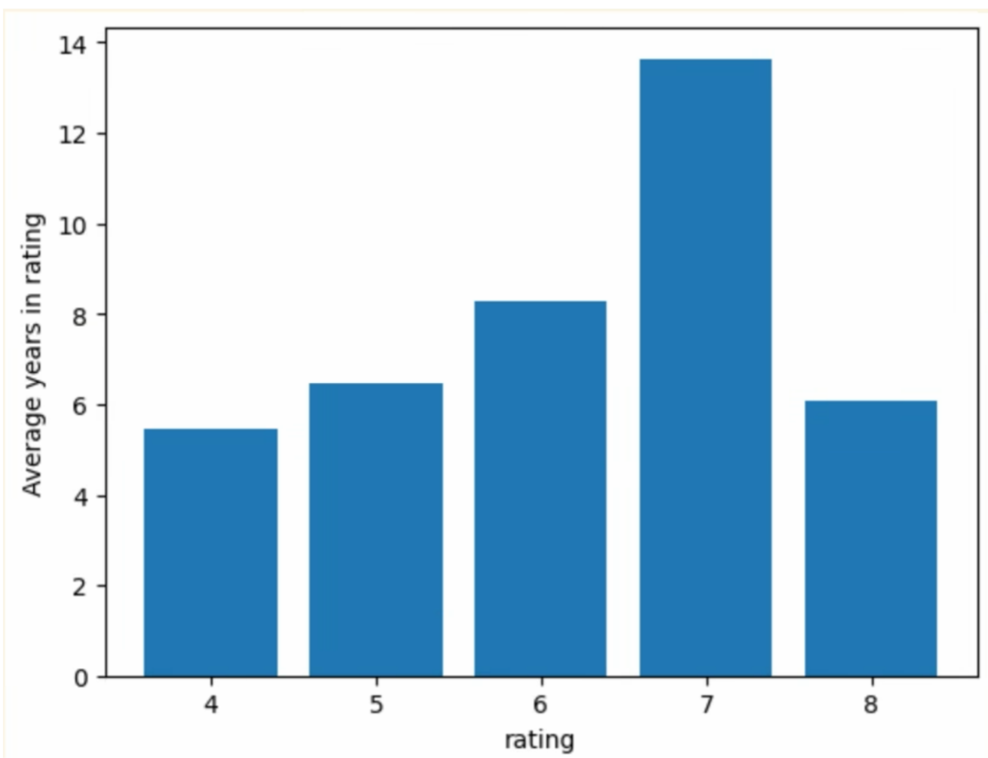
5.2.1 The Rate of Bridge Deterioration

To assess the rate of bridge deterioration, we conducted a statistical analysis of both historical and prediction data. We consider the duration for which bridges maintain a rating of 5 as an effective indicator of deterioration speed. A shorter duration at rating 5 signifies a faster rate of deterioration.

As shown in Figure 43(a), the existing data from 1992 to 2021 indicates that, on average, a bridge will remain at a rating of 5 for 6.46 years. In contrast, our 30-year prediction (2022 to 2051) suggests an average duration of 7.74 years at rating 5, which is approximately one year longer. Additionally, the historical data shows that bridges maintain a rating of 7 for the longest period, averaging 13.64 years, whereas our predictions show an average duration of 12.04 years. The figure also indicates that bridges will remain at rating 4 for the longest period in our predictions, as at condition ratings of 4 or below, the model no longer considers deterioration.



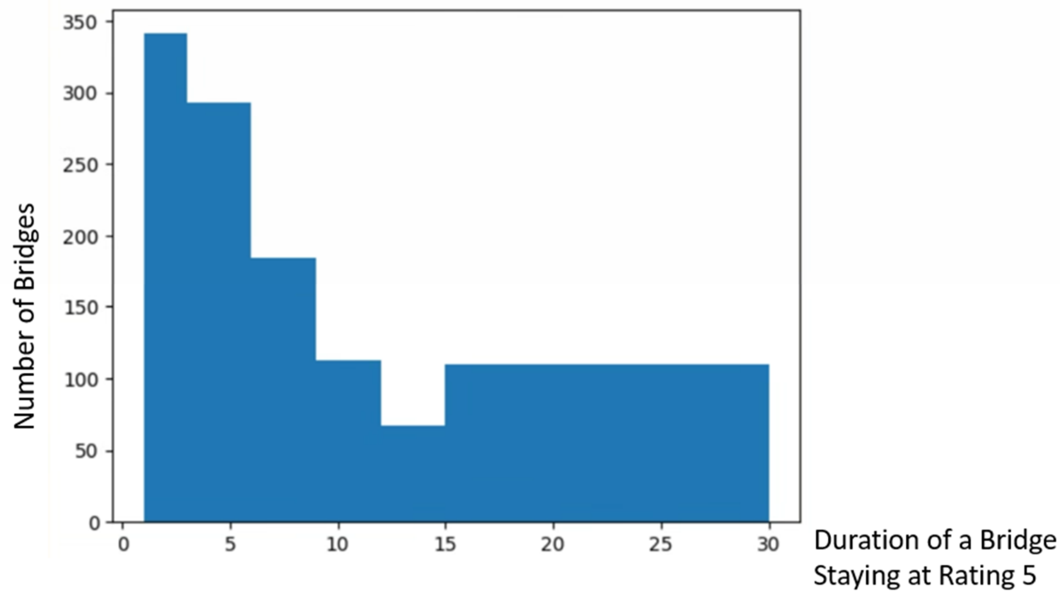
(a) Historical Data (1992 – 2021)



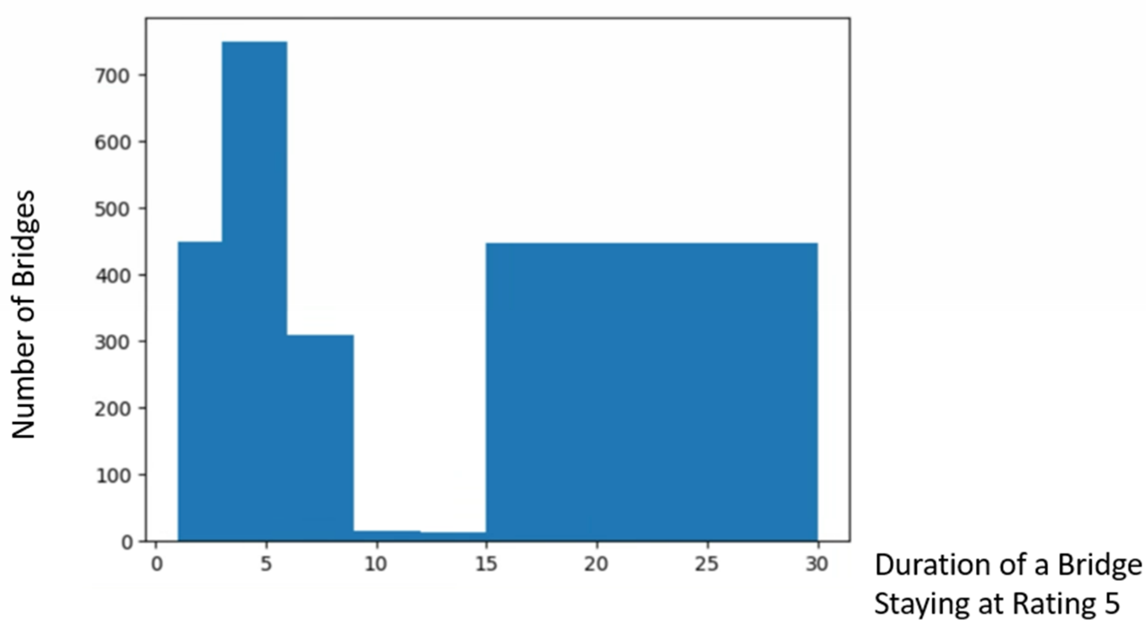
(b) Model Prediction (2022 – 2051)

Figure 43 Average Duration of Bridges Maintaining a Rating

Figures 44(a) and 41(b) illustrate the distribution of bridges, specifically the number of bridges, for durations of 5, 10, 15, 20, 25, and 30 years at a rating of 5. Both historical and prediction data reveal similar patterns. The historical data indicates that more than 300 bridges remain at rating 5 or lower, while prediction data shows that more than 700 bridges are rated 5. However, the prediction results also reveal that only a few bridges stay at rating 5 for 10 to 15 years. Despite this, both datasets exhibit similar distribution patterns.



(a) Historical Data (1992 – 2021)



(c) Prediction Data (2022 – 2051)

Figure 44 Historical Data vs. Prediction Data – Bridge Distribution in terms of the Duration of Bridge Staying at Rating 5

5.2.2 Case Studies

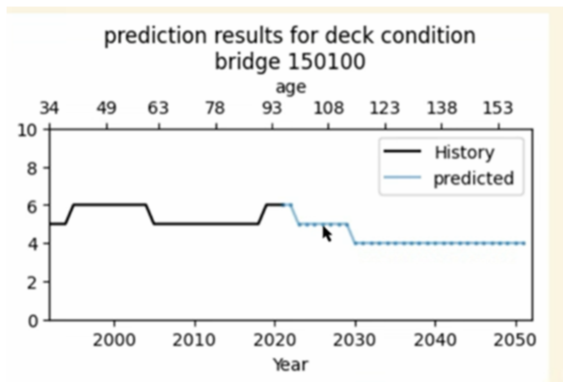
Below are case studies of a few randomly selected bridges, presenting their predicted results:

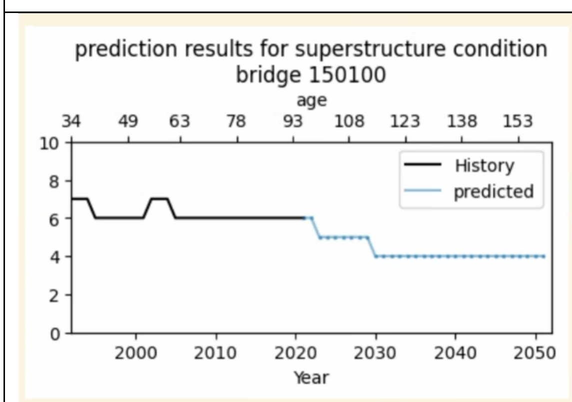
<u>Case 1 - Bridge 00016 (Structural ID for the Project: 150100)</u>

As shown in Figure 45, this bridge, located on Riverside Avenue in Riverside, CT, crossing I-95, is constructed of steel continuous, Stringer/Multi-beam or Girder. The deck, superstructure, and substructure exhibit similar deterioration patterns. The predictions indicate that the bridge rating will drop from 6 to 5, staying at 5 for about 6 years before descending to 4. This research ceases predictions once the bridge reaches a rating of 4. In this case, the bridge age might play a significant role in determining its deterioration pattern.

Structure id: 150100

i	COLUMN_NAME	VALUE
6	LAT_016	41021904.0
7	LONG_017	73351252.0
16	DESIGN_LOAD_031	5.0
32	STRUCTURE_KIND_043A	4.0
33	STRUCTURE_TYPE_043B	2.0
36	MAIN_UNIT_SPANS_045	2.0
39	MAX_SPAN_LEN_MT_048	27.1
40	STRUCTURE_LEN_MT_049	55.8
75	YEAR_RECONSTRUCTED_106	0.0
76	DECK_STRUCTURE_TYPE_107	1.0
13	YEAR_BUILT_027	1958.0





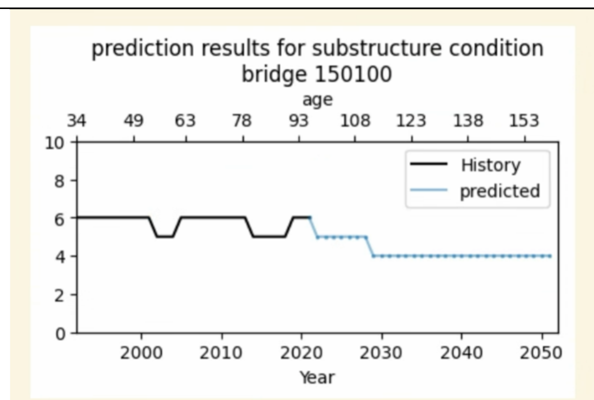


Figure 45 Bridge 00016 (Structural ID for the Project: 150100), Historical and Predicted Ratings

Case 2 – Bridge 04969 (Structure ID for the Project: 30860100)

Figure 46 presents the prediction results for another steel bridge. This bridge demonstrates a longer duration at a rating of 5 for the deck, superstructure, and substructure. For the superstructure condition, considering the bridge's rating has already dropped to 3, the model predicts an increase in the rating, taking into account potential repairs and other human interventions. This bridge suggests a longer duration of 17 years at a rating of 5 compared to Case 1. Although the bridges in Case 1 and Case 2 are of similar age, the bridge in Case 2 has a shorter structure and span length.

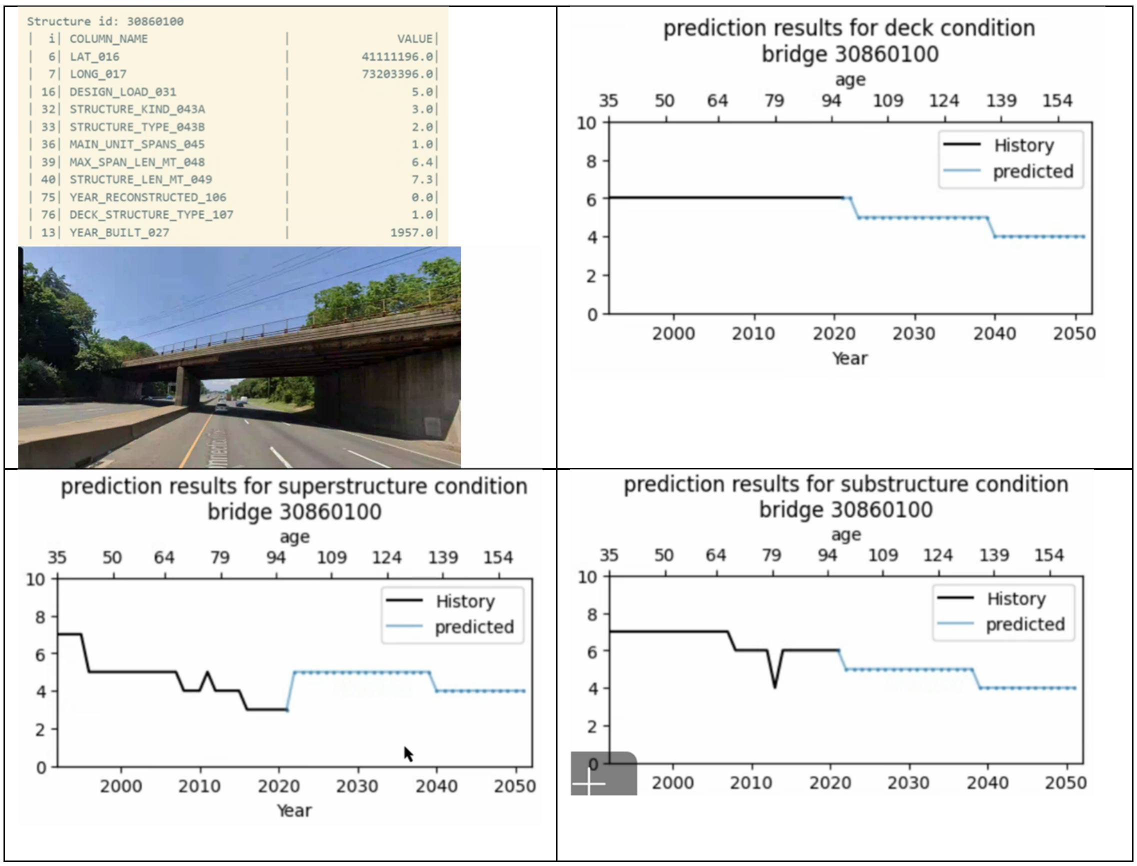
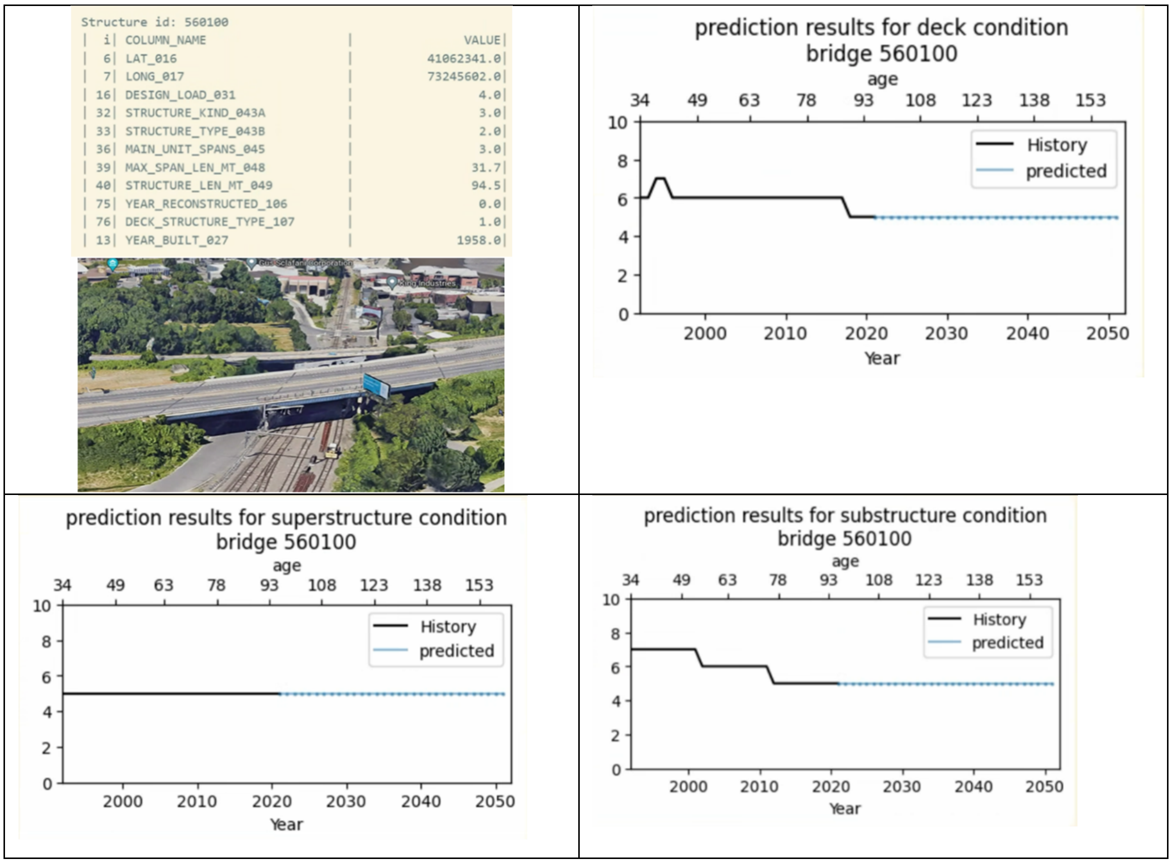


Figure 46 Bridge 04969 (Structure ID for the Project: 30860100), Historical and Predicted Rating

Figure 47 presents the historical (1992-2021) and predicted (2022-2121) ratings of the deck, superstructure, and substructure of Bridge 00058. Over the past 30 years, from 1992 to 2021, the deck and substructure have maintained relatively steady ratings of 6 or 5, while the superstructure has declined from 7 to 5. The prediction results indicate that this bridge will continue to maintain a rating of 5 for the next 30 years.

<u>Case 3 – Bridge 00058 (Structure ID for the Project only: 560100)</u>


Structure id: 560100

i	COLUMN_NAME	VALUE
6	LAT_016	41062341.0
7	LONG_017	73245602.0
16	DESIGN_LOAD_031	4.0
32	STRUCTURE_KIND_043A	3.0
33	STRUCTURE_TYPE_043B	2.0
36	MAIN_UNIT_SPANS_045	3.0
39	MAX_SPAN_LEN_MT_048	31.7
40	STRUCTURE_LEN_MT_049	94.5
75	YEAR_RECONSTRUCTED_106	0.0
76	DECK_STRUCTURE_TYPE_107	1.0
13	YEAR_BUILT_027	1958.0

Figure 47 Bridge 00058 (Structure ID for the Project: 560100) Historical and Predicted Rating

5.3 Bridges with Potential Risks

Figure 48 illustrates the number of bridges projected to have ratings of 3 or lower, 4 or lower, 5 or lower, 6 or lower, and 7 or lower over the next 30 years. By 2051, it is anticipated that2,083 bridges will have superstructure ratings that drop to 5 or lower. We consider a bridge rating of 5 to indicate potential risks. A bridge rating dropping to 5 or lower is a critical stage in understanding bridge condition. Figure 49 illustrates the rate at which the number of bridges with ratings dropping to 5 or lower will increase every 10 years over the next 60 years. Between 2013 (10 years) and 2041 (20 years), the ratings of over 100 bridges are predicted to drop to 5 or lower. After 2041, the number of bridges with ratings dropping to 5 will continue to increase by approximately 40 to 60 bridges every 10 years.

The complete list of bridges projected to have ratings of 5 or lower within the next 30 years is provided in Appendix B. Figures 50 and 51 highlight some characteristics of these bridges.

Using the next 30 years as an example, Figure 50 illustrates the age distribution of the 2,083 bridges. Approximately 70% of these bridges are over 84 years old. Notably, 935 of these bridges, nearly half, fall within the age range of 84 to 102 years.

Figure 51 shows that among the 2,083 bridges, more than half are made of steel and steel continuous, followed by concrete and prestressed concrete.

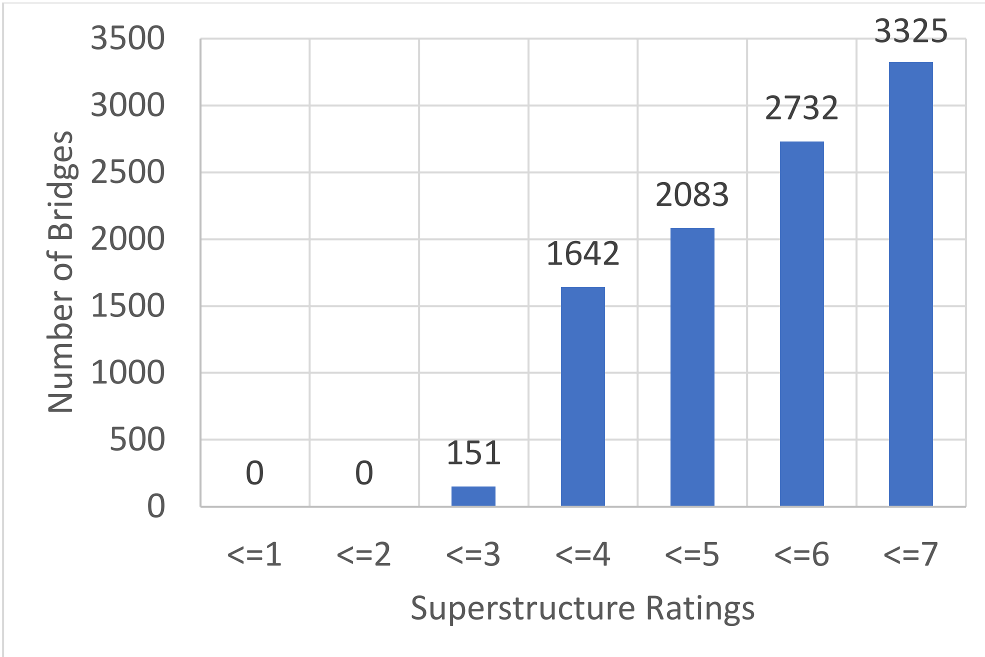


Figure 48 Number of the Bridges with Superstructure Ratings within 30 Years (2022 – 2051)

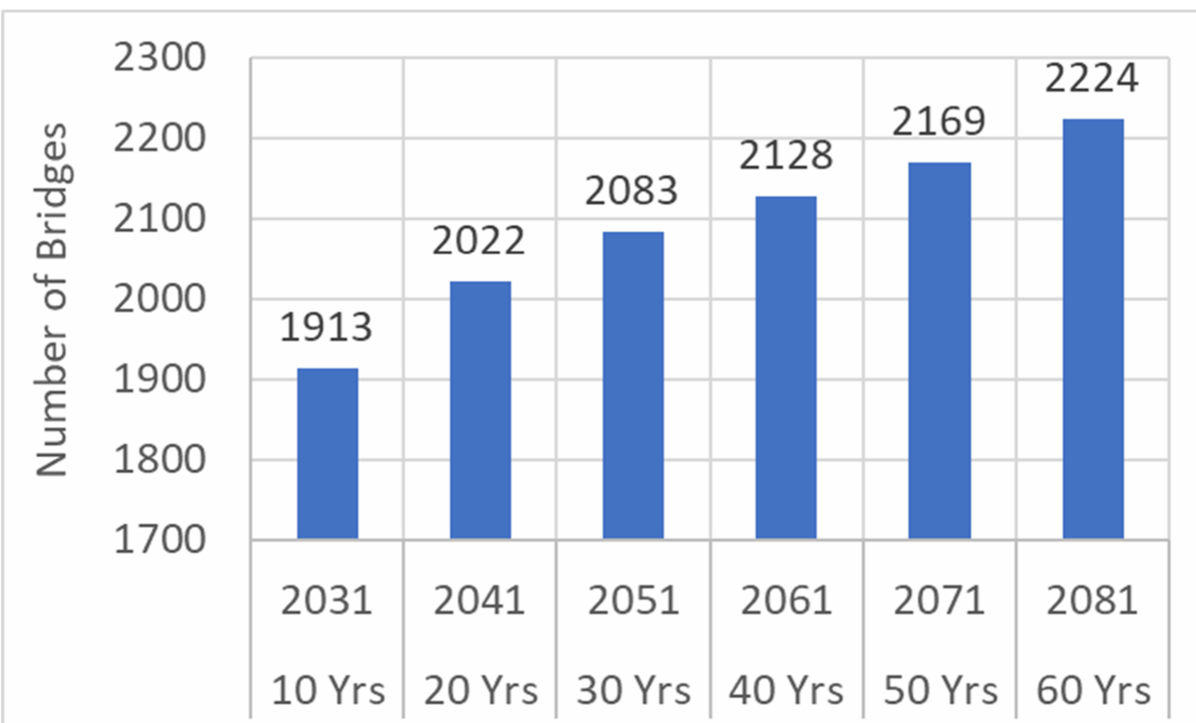


Figure 49 Number of the Bridges with Ratings Dropped to 5 or Lower

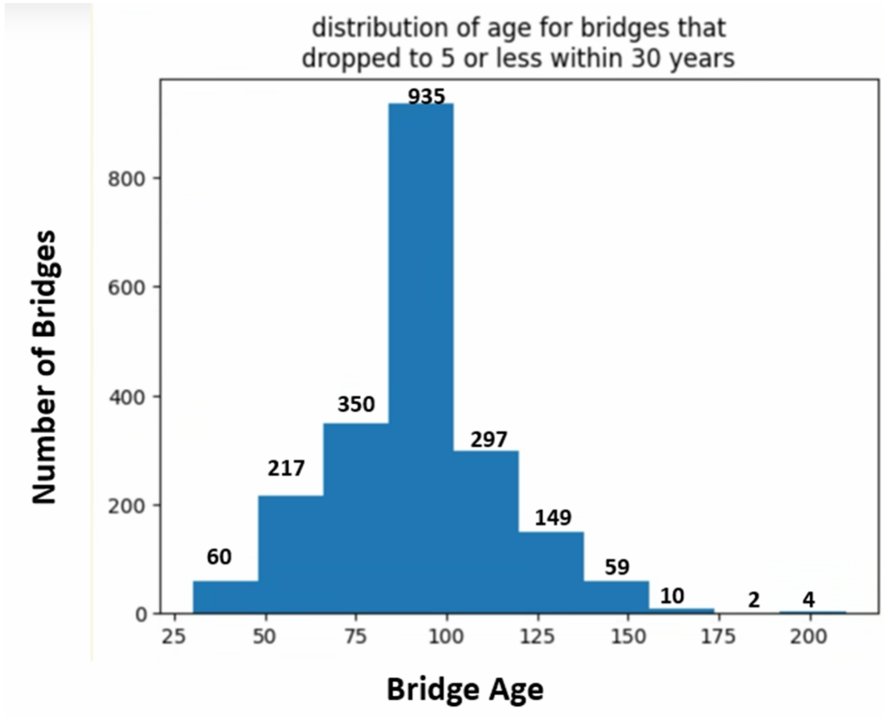


Figure 50 Number of Bridges Having Rating Drop to 5 with Respect to Bridge Ages

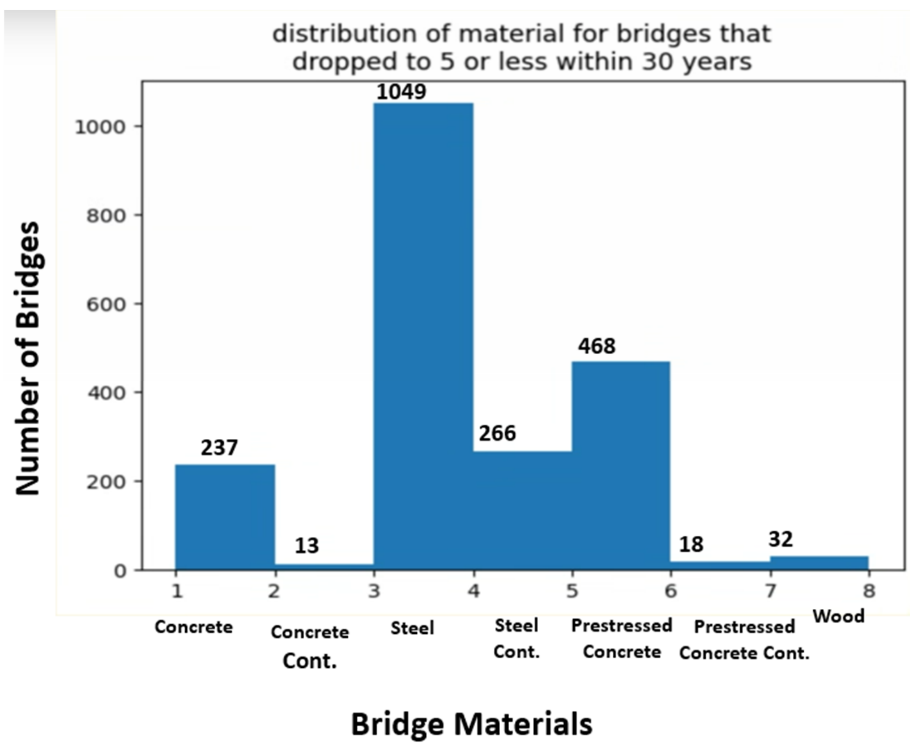


Figure 51 Number of the Bridges with Respect to Bridge Materials

CHAPTER 6 CONCLUSIONS, DELIVERABLES AND RECOMMENDATIONS

6.1 Conclusions

This project represents a significant advancement in bridge management decision-making and preventive maintenance strategies through the application of artificial intelligence deep learning models to predict future bridge condition ratings. By leveraging historical inspection data, we have developed a robust framework capable of forecasting bridge conditions up to 100 years into the future.

The data collected from the National Bridge Inventory (NBI), encompassing various aspects such as location, design, condition, and usage, formed the foundation for our model. Through meticulous data processing, reformatting, and transformation, we addressed challenges inherent in predicting bridge condition ratings, including heterogeneous data sources, complex high-dimensional data, and mixed data types.

Our approach, grounded in deep neural networks, effectively tackled these challenges. By employing an autoencoder neural network and a long short-term memory (LSTM) recurrent neural network (RNN), we compressed high-dimensional categorical and sequential data into lower-dimensional latent features. These latent features served as inputs to a multi-layer perceptron (MLP) network, which produced the final bridge condition rating predictions. The two-stage training process, where the autoencoder, LSTM, and MLP networks were trained and tuned separately, ensured the accuracy and reliability of our predictions.

The pre-trained model was applied to conduct a comprehensive study of all bridges in Connecticut, providing valuable insights into their future conditions. The predicted results are organized into deterioration trends for all bridges, individual bridge deterioration curves, and identification of bridges with potential risks. This detailed analysis facilitates informed decision-making and the implementation of effective maintenance strategies, ultimately contributing to the safety and longevity of the state's bridge infrastructure.

In conclusion, our project successfully demonstrates the potential of advanced machine learning techniques in enhancing bridge management and maintenance. By predicting future bridge conditions with high accuracy, we provide a powerful tool for CT DOT and other stakeholders to proactively address potential issues and ensure the sustained integrity of bridge structures.

6.2 Deliverables

Below is a comprehensive list of the project deliverables:

- Final Project Report: A detailed document encapsulating the research methodology, model development, data analysis, and findings.
- Bridge Prediction Results for the Next 30 Years:
  - NBI Data Format in Excel Spreadsheet: Organized data in the National Bridge Inventory (NBI) format, facilitating easy access and analysis.
  - Individual Bridge Deterioration Curves: Accessible through the developed website, showcasing the deterioration trends for each bridge. The website also includes the probability distribution for each rating.
- List of Bridges with Potential Risks in the Next 30 Years: A detailed list identifying bridges projected to have their ratings drop to 5 or lower, highlighting those that may require immediate attention and maintenance.

6.3 Recommendations

a) Incorporating Actual Data into Future Predictions

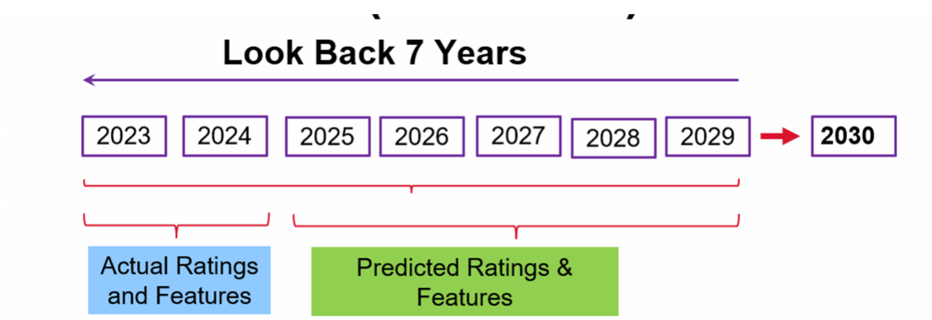


Figure 52 Rating Prediction Model by AI

The AI model developed in this research employs a seven-year look-back period, as shown Figure 52. For example, to predict bridge ratings for 2030, the model uses data from 2023 to 2029, generating predictions year by year. Currently, the model utilizes predicted data for each of these seven years to achieve the 2030 prediction. However, when actual data for some years within this seven-year window are available—such as 2023 and 2024—the model should be capable of integrating these real-life data points into its predictions. Incorporating actual data can enhance the accuracy and reliability of the prediction outcomes.

In addition, the model's ability to account for time in its predictions can enhance model realism. By incorporating the duration a bridge has remained in its current state, we can slow down this predicted decline and create more realistic projections. This temporal aspect allows for a better understanding of the relationship between time and bridge condition, ultimately leading to more informed model.

b) Applying Monte Carlo Sampling Technique

The project has explored the potential of applying the Monte Carlo sampling technique to select a rating from the probability distribution. Unlike traditional methods that use the rating with the highest probability, the Monte Carlo technique introduces randomness into the prediction process. This approach can provide a more realistic range of possible outcomes, enhancing the robustness of the predictions.

c) Considering Weather and Environmental Factors

Weather features such as temperature, precipitation, atmospheric pressure, and wind speed play a crucial role in the bridge deterioration process. In the New England area, applying salts on bridge surfaces during winter can also impact the rate of deterioration. Future research should consider incorporating these weather and environmental factors into AI deep learning to improve its accuracy and relevance.

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Appendix A:

Predicted Conditional Ratings for Connecticut Bridges Over 30 Years (2022 – 2051)

This appendix presents the predicted conditional ratings for the deck, superstructure, and substructure of Connecticut bridges over 30 years from 2022 to 2051. The data is provided in an Excel spreadsheet formatted according to the National Bridge Inventory (NBI) standards.

Appendix B:

Bridges Projected to Have Ratings of 5 or Lower Within the Next 30 Years

This appendix provides a comprehensive list of bridges anticipated to receive conditional ratings of 5 or lower within the next 30 years, highlighting those that may require significant maintenance or rehabilitation. They are provided in an Excel Spreadsheet.