Predictive Modeling of Effect of Weather Conditions on Road Construction Projects in USA

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Abstract

Although sophisticated tools exist for predicting future weather conditions, how these measurements combine to systematically affect project duration is quite intractable. To tackle complex predictive modeling problems, Artificial Intelligence (AI) and Deep Neural Networks (DNN) have been applied over the years to develop sophisticated predictive models from measured data. AI and DNN leverage the classical concepts of regression, back-propagation, and optimization to fit a mathematical model to data. For a successful model to be realized via AI and DNN approaches, some knowledge of the parameters that affect the variable to be predicted is required. The exact mathematical or physical relationship between weather conditions and project duration is unknown in this study. The weather parameters that could affect project duration are studied via Exploratory Data Analysis (EDA), and the length of the road construction is explored as a pertinent feature too. The results of EDA enabled the development of a DNN model for predicting project durations as short-, medium-, or long-term. Furthermore, the authors discovered an almost equal chance of classifying projects into the above-listed categories leveraging the discovered features from EDA. This result is attributed to the ill-definition of project duration classes, the uncertainties in the data acquisition process, and the representation of the dataset obtained from Kaggle's website.

1.0 Introduction

A nationwide dataset of road construction and closure events, including data from 49 US states is chosen for the project. The projects included in this dataset's ranges from minor paving repairs to significant undertakings that might take months to complete. Several APIs that provide streaming traffic incident (or event) data were used to collect the data between January 2016 and December 2021. These APIs transmit traffic information gathered by several organizations, including the US and state departments of transportation, law enforcement organizations, traffic cameras, and traffic sensors embedded in the road networks. The number of construction and shutdown records in this dataset currently stands at roughly 6.2 million.

Intuitively, one would imagine that harsh weather conditions would affect the duration of a road construction project. Moreover, project durations could be quantitatively classified as short-, medium-, or long-term based on suitable thresholds that map project duration (in days) to the underlisted classes. Although sophisticated tools exist for predicting future weather conditions, how these measurements combine to systematically affect project duration is quite intractable. To tackle complex predictive modeling problems, Artificial intelligence (AI) [1] and Deep Neural Networks (DNN) [2] have been leveraged over the years to develop sophisticated predictive models from measured data. AI and DNN leverage the classical concepts of regression [3], back-propagation [4], and optimization [5] to fit a mathematical model to data. For a successful model to be realized via AI and DNN approaches, some knowledge of the parameters that affect the variable to be predicted is required. The exact mathematical/physical relationship between weather conditions and project duration is unknown in this study. Therefore, the weather parameters that could affect project duration are studied via exploratory data analysis (EDA) [6], and the length of the road construction is explored as a pertinent feature. The results of EDA enabled the development of a DNN model for predicting project durations as short-, medium-, or long-term.

For this study, a nationwide dataset of road construction and closure events, including data from 49 US states, is chosen for the project. The road work included in this dataset's construction events ranges from minor paving repairs to significant undertakings that might take months to complete. Several APIs that provide streaming traffic incident (or event) data are used to collect the data between January 2016 and December 2021. These APIs transmit traffic information gathered by several organizations, including the US and state departments of transportation, law enforcement organizations, traffic cameras, and traffic sensors embedded in the road networks. The number of construction and shutdown records in this dataset currently stands at roughly 6.2 million. In general, this dataset can be used for a wide range of applications, including the prediction of short- and long-term road construction, the prediction of road closures, the study of the life cycle of road construction, the development of insights to help city planners choose construction sites wisely with the most negligible negative impact on traffic flow, and the investigation of the influence of precipitation or other environmental stimuli on the need for road work [7]. The dataset is being updated on an annual basis. The data will be obtained from Kaggle [8], which is available in CSV format. Presently, the dataset contains 6,170,627 observations comprising features like Construction severity, Latitude, longitude, Precipitation, Traffic signal, etc., resulting in a total of 47 columns. Table 1 elaborates on the description of this data set.

This dataset is used to develop a DNN model to predict the duration of a new road construction project as short, medium, or long-term, given inputs of pertinent features derived from Table 1. The developed model is then validated and tested to be made suitable for accurate and robust predictions. With this model, it is envisaged that contractors, city planners, and relevant authorities can categorize potential road construction projects based on expected average weather conditions for better planning and project delivery. This study explains how data wrangling is performed to clean, manipulate and make the obtained data suitable for EDA in section 2. Section 3 elaborates on a methodology for developing a DNN to map measurements to predictions, and finally, the study is concluded in section 4 with a discussion of our results and proposal for future study. In the end, an appendix section is included, which comprises relevant tables and plots.

Table 1: Description of dataset

Features	Description
ID	Unique identifier of construction record
Severity	Shows the severity of the construction
Start and End Time	Shows the start time of construction
End Time	Shows the end time of construction
Latitude and Longitude	Shows the GPS coordinates
Distance	The length of the road extent affected by the construction
Street Details	Shows the street number, name and right/left side in address field
Address Details	Shows the city, county, state, country and zip code in address field
Time zone	Shows time zone based on the location of the construction event
Weather	Shows the time stamp of weather observation record
Temperature, Wind, Humidity, and Pressure	Shows the temperature, wind chill, humidity, and pressure
Visibility	Shows visibility

Features	Description
Wind Direction and Speed	Shows wind conditions
Precipitation and Weather condition	Shows precipitation and weather condition
Amenity	An annotation which indicates presence of amenity in a nearby location
Bump and Crossing	Annotations which indicate presence of speed bump or hump and crossings
Give way, Junction, railway	Annotations which indicate presence of give way, junction and railway
Exit, Roundabout, Station, Stop	Annotation which indicates presence of no exit, railway, roundabout, and station
Traffic Details	Annotations which indicate traffic calming, signal, turning loop
Light Details	Annotations which indicate sunrise, sunset, civil twilight, nautical twilight, astronomical twilight

2.0 Data Wrangling and Exploratory Data Analysis

The data set obtained from Kaggle is highly generic and unstructured, which limits the outcome if used as it is in predictive modeling. To ensure the data is reliable and complete, data wrangling is performed to derive maximum insights from it, making it qualitative data suitable for analysis. EDA was later used to explicitly identify the pertinent features affecting the duration of road construction.

2.1 Data Cleaning

The original data set was composed of 6.1 million observations, which is computationally expensive to work with given time constraints. Given the scope of work and time availability, the idea is to reduce the data to a computationally amenable size. Based on the random guess, 15% of the original data is selected for the analysis ignoring the rest, 85% of the data. In addition, the data frame obtained from this data had some missing entries, which were removed, further reducing the size of the data set to 482,849 observations. Also, the selected data frame needed cleaning of any Boolean and Strings values before EDA. Fig. 14 in the appendix shows the summary of the cleaned dataset.

2.2 Data Wrangling

The data to the naked eye was still unsatisfactory as features like project duration were not explicitly mentioned; instead, project start- and end-time were described as two different features. Using Julia's syntax, a new feature termed "Project Duration Days" is computed by taking the difference between respective project start and end times. Fig. 15 in the appendix shows how this data looked before and after performing data wrangling in specifics to project duration. After obtaining the project duration and reading it in parallel with the road length, some observations did not seem realistically possible. For instance, one of the rows shows that a road length of 1.1035 miles takes more than a year to complete its construction, which is not realistic if analyzed through the lenses of civil engineering. The original data set was further investigated to conclude that the data set also includes road repair work in addition to the new road construction. Unfortunately, the dataset has no feature that reveals if an observation was a minor repair task or a primary construction task. To circumvent this, observations corresponding to project durations less than 50 days are filtered out, resulting in a dataset of 43,134 observations significantly dominated by new road construction projects or at least projects lasting longer than 50 days.

The project duration is further categorized into short-, medium- and long-term road construction projects to better suit our predictive modeling. For this project, a short-term road construction project is defined as one lasting less than 100 days, a medium-term project lasts between 100-300 days, and a long-term project lasts longer than 300 days. Fig. 16 in the appendix showcases how the data set looks after applying the classification to the project duration.

2.2.1 Feature Detection and EDA

The resulting dataset, as presented in Fig. 16 of the appendix, is processed to reveal critical features. A rough guess is that the features quantifying environmental conditions like temperature, wind chill, pressure, and humidity together with the road construction span affect the project duration as there is a considerable spread in their histogram distributions. It is assumed that the recorded values of these environmental features are an average over the entire project duration. Thus, given the average environmental conditions and the span of road construction, the developed model is expected to predict the class of the project's completion time as short, medium, or long-term. Table 2 below shows the summary of features selected for the predictive model.

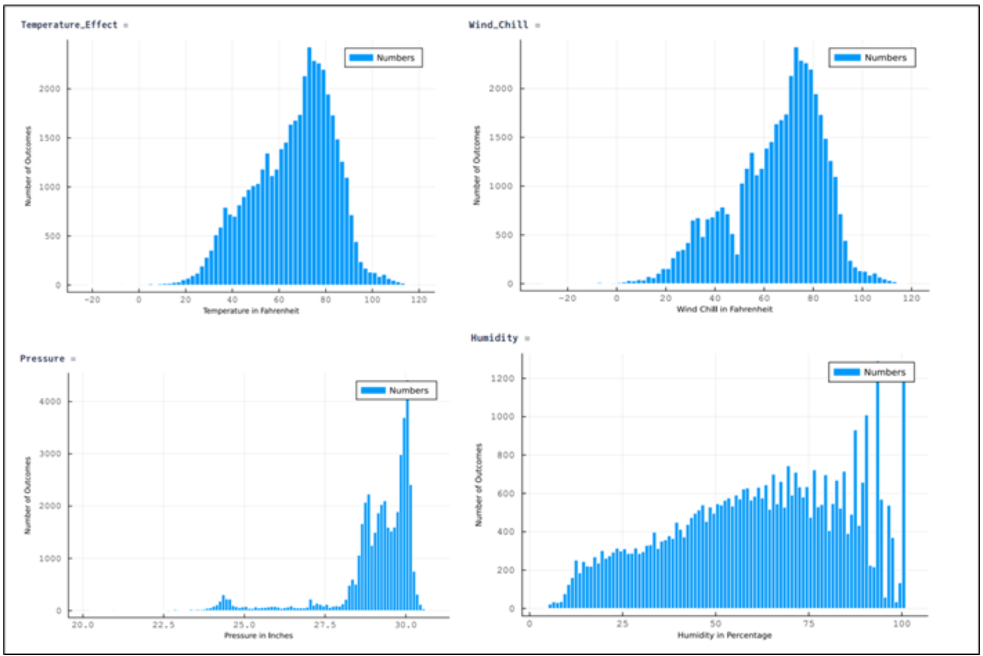


Fig. 1: Histogram plots showing spread of Temperature, Wind Chill, Pressure and Humidity in the selected dataset

Table 2: Extracted features for performing EDA

	Distance(mi)	Temperature(F)	Wind_Chill(F)	Humidity(%)	Pressure(in)	Visibility(mi)	Wind_Speed(mph)	Precipitation(in)	Project_Duration_Days
1	1.1035	75.0	75.0	58	29.72	10.0	3.0	0.0	544
2	1.10024	70.0	70.0	60	28.89	10.0	5.0	0.0	94
3	0.952071	48.0	46.0	93	29.72	2.0	5.0	0.01	215
4	0.24557	72.0	72.0	78	29.88	10.0	8.0	0.0	411
5	0.453084	64.0	64.0	87	29.37	4.0	0.0	0.0	97
6	0.601812	73.0	73.0	87	29.1	7.0	6.0	0.0	297
7	0.173348	50.0	50.0	31	28.68	10.0	6.0	0.0	305
8	0.380199	71.0	71.0	84	29.95	10.0	0.0	0.0	245
9	0.118257	79.0	79.0	66	30.17	10.0	12.0	0.0	182
10	0.701292	41.0	41.0	65	29.15	10.0	3.0	0.0	162
⋮ more									
43134	0.999269	70.0	70.0	90	29.09	10.0	0.0	0.0	104

2.2.1 Feature detection and EDA

The data presented in Table 2 is a dataset that is easier for all the subsequent working. It currently comprises eight independent features, with project duration as the dependent feature. An indispensable aspect of EDA is detecting multicollinearity and preventing modeling confounding. Therefore, Julia's "Statistics" package is leveraged to compute and plot the correlation between all the independent and the dependent variables. This plot enabled the discovery of statistically related features. The figures (Fig. 2 through Fig. 5) below show the correlation plots for the selected features. The "Combinatorics" package in Julia is leveraged to create three (3) combinations of all features, including the dependent variable. A total of fifty-six (56) combinations were generated and plotted in Julia.

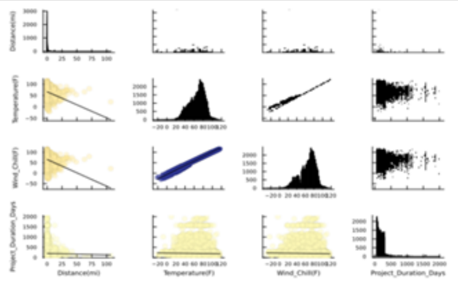


Fig. 2: Correlation plot for Distance, Temperature, Wind chill and Project Duration

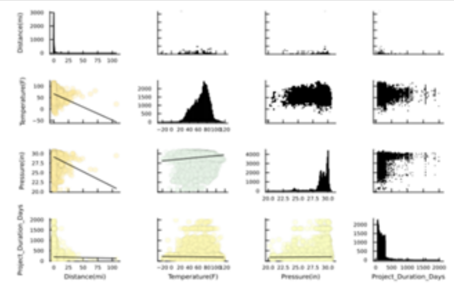


Fig. 3: Correlation plot for Distance, Temperature, Pressure and Project Duration

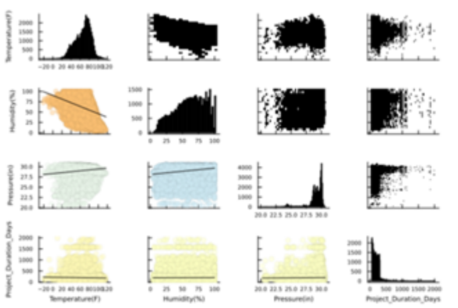


Fig. 4: Correlation plot for Temperature, Humidity, Pressure and Project Duration

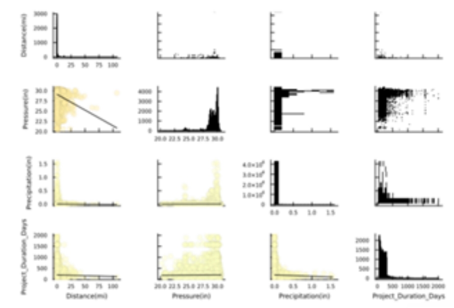


Fig. 5: Correlation plot for Distance, Pressure, Precipitation and Project Duration

Following the correlation plots above, the scatter plots, as shown in Fig. 6, are plotted, showing promise in developing a classification tree or neural network.

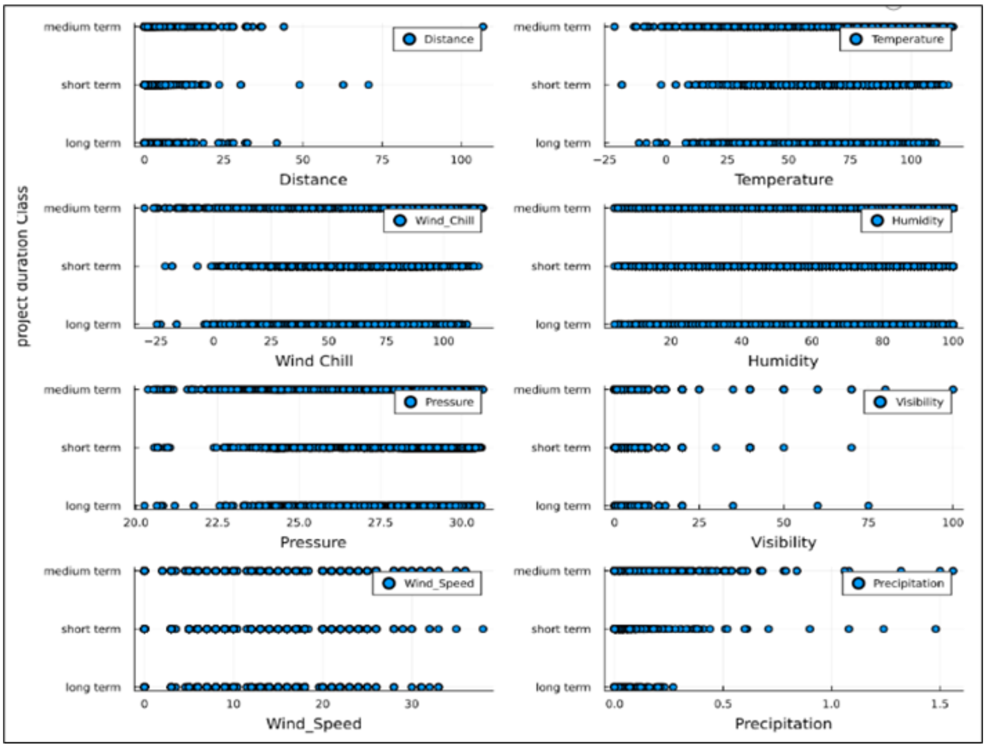


Fig. 6: Scatter plots of pertinent features against Project Duration Class

Despite Fig. 6 revealing Humidity as a less promising feature for the project task, all features will be considered in the model development. Additionally, as shown in Fig. 7, the following box plots reveal outliers in all the feature spaces except for Humidity. A further investigation of the statistical significance of selected features is done through Principal Component Analysis (PCA) which enables possible dimensional reduction of the model.

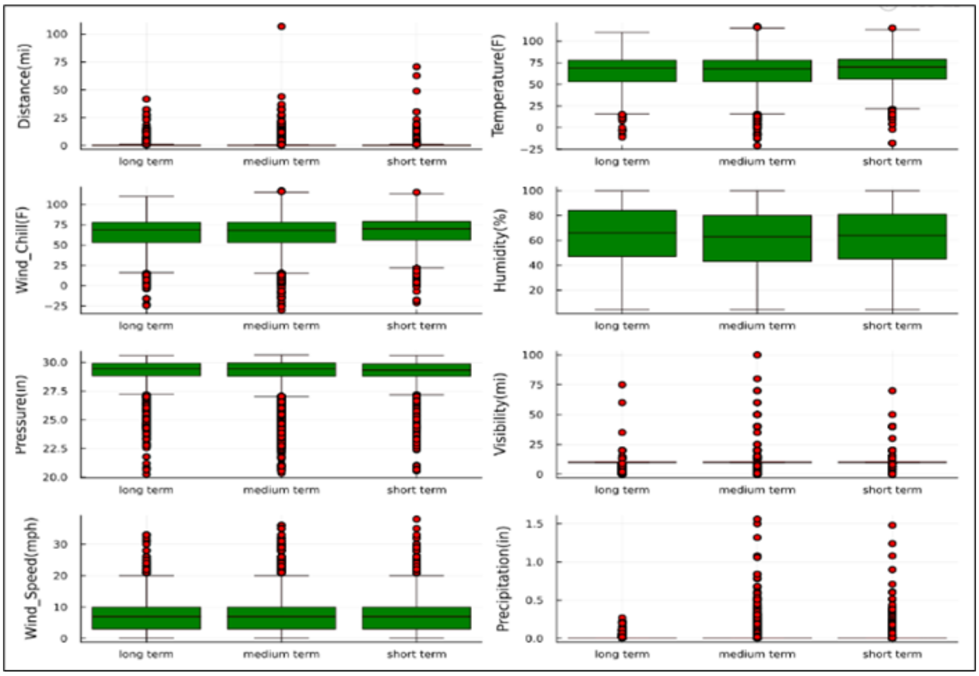


Fig. 7: Box plots for outlier detection in pertinent features

2.3 Dimensionality Reduction

PCA is performed to get a concise dataset representation, improve the model accuracy, and transform the data set. This analysis captured 97% of the variance in the original dataset with just two principal components, which is a good representation of the original data. Furthermore, it dramatically reduced the number of features to two, hinting at a strong possibility of a classification model.Outlier analysis too is done to identify outliers in the PCA coordinate frames for tuning and feature selection. These scatter plots with the outlier detection analysis are presented in the appendices for better understanding. A quick overview makes one feel that the first two principal components would be sufficient for the classification task. However, this is not the case. The plots in Fig. 17 in the appendix reveal that the 4th, 5th, 6th, 7th, and 8th PCA coordinate frames, too, offer significant promise for the project goal. Fig. 17 and Fig. 18 of the appendix showcase that cuts can be readily made to develop robust decision trees based on the Gini-impurity algorithm [9], or a Deep Neural Network could be easily employed.

3.0. Model Development and Evaluation

3.1 Datasets for model development

Based on EDA performed on the selected data set, a predictive model is built on seven potential weather features and the road construction length ("Distance" in miles) – making a total of 8 input features – to predict the duration of road construction as "short term", "medium term", or "long-term" project. These features include temperature, wind chill, humidity, pressure, visibility, wind speed, precipitation, and distance.

To initiate the predictive modeling, the wrangled dataset comprising pertinent features was randomly split into training set, testing set, and validation set having 60%, 20%, and 20% observations respectively. To ensure the efficiency of predictive modeling, three kinds of datasets from the wrangled data were considered. The first dataset (case 1) was derived by defining the project duration as "short-term" if the project duration is less than 100 days, "medium-term" if the project duration is between 100 through 300 days and "long-term" if the project duration is greater than 300 days. The second dataset (case 2) is the PCA transformation of the first dataset's features. Lastly, the third dataset (case 3) defines a "short-term" project as one with a project duration less than 120 days, "medium-term" if the project duration is between 120 through 200 days, and "long-term" if the project duration is greater than 200 days. The third dataset was explored because the initial results of the first dataset were not very satisfactory, and the determination of these thresholds is quite ambiguous.

3.2 Methodology

For the model development, a deep neural network (DNN) architecture – the sequential model from the Keras library in Tensorflow was leveraged [10]. DNN was resorted due to the high dimensionality of the feature-space and the non-existence of a physical model that relates weather conditions to road construction project duration. Hence with DNN, patterns in the data feature space would be automatically realized, weights would be generated to fit a model to the data and predict the output (project duration labels) given inputs of weather conditions (Temperature, Pressure, etc.) and road length. This sequential model accepts a single tensor of features and observations and returns a single tensor of labels for each observation as its output. Furthermore, the Keras library offers various loss functions depending on the kind of model to be built. The categorical cross-entropy loss function [11] was leveraged for multi-class classification for this project. Python offers great flexibility and computational speed when addressing multi-class classification problems; hence it was adopted for model development. Additionally, R was leveraged to validate the modeling process with Python, and the results obtained agree with those of Python. The confusion matrix plots obtained from R are attached as Fig. 19 and Fig. 20 in the appendix of this report. The labels from the dataset (i.e., the dependent variable which is the project duration class) is represented in the one-hot [12] format. To get the intended predictions, three hidden layers with 32, 64 and 128 neurons respectively were initially defined. However, the final architecture included seven hidden layers as the initial three hidden layers resulted in only 65% training accuracy, which was considered suboptimal. Also, we tuned parameters like regularization, epoch (number of gradient descent steps, and batch size to enhance the process of building and training the neural network. Regularization was tuned between 1e-3 and 1e-6 for various trials, epoch was tuned to 500, and batch size was tuned to 10. These parameters were chosen based on recommendations by [13].

Additionally, the activation function between hidden layers was set to ReLU [14], since the input data were mainly numerical data that is continuous in space. However, the sigmoid [15] activation function was used between the last hidden layer and the output, because the output is categorical i.e., "short-term", "medium-term" and "long-term". This sigmoid function computes the probability of occurrence of each label per observation, that ranges from 0 through 1. The predicted label from various observations is the one that has maximum output probability and is assigned as 1, keeping other labels as 0. To enhance global optimality, stochastic gradient descent "sgd" [16] was also tried as the learning rate function in the model development.

3.3 Results

Having completed the model preparation and training, the open-source Sklearn [17] package was leveraged to calculate prediction metrics like precision, recall, and f-score for each class, on the test dataset and plot confusion matrix for visualization. The confusion matrix plots and accuracy metrics after testing the models on the various test and validation datasets are presented below.

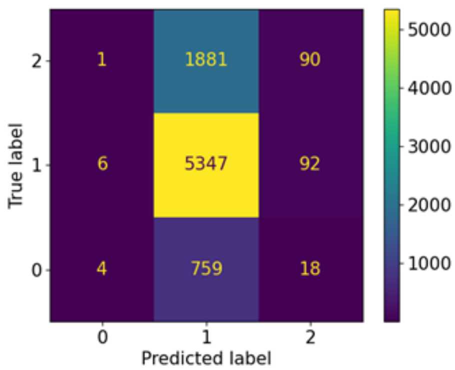


Fig. 8. Confusion matrix for case 1 test dataset, with 3 hidden layers of 32, 64, and 128 neurons respectively

Outcome from Fig. 8: 65% accuracy was obtained on the training data, with a loss of about 0.6. The accuracy on the training dataset was suboptimal and hence, no testing was performed on this dataset.

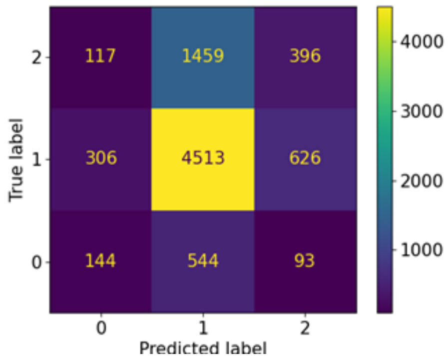


Fig. 9. Confusion matrix for case 2 test dataset, with 7 hidden layers with 32, 64, 128, 256, 128, 64 and 32 neurons respectively

Outcome from Fig. 9: 87% accuracy was obtained on the training data

Prediction Matrix	Description
Precision	0.35, 0.66, and 0.26 for short term, medium term and long term respectively
Recall	0.22, 0.72, 0.19, for short term, medium term and long term respectively
Proportion of each class in original dataset	25%, 65% and 0.1% for short term, medium term and long term respectively

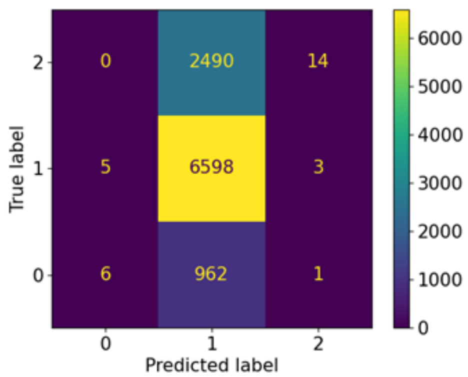
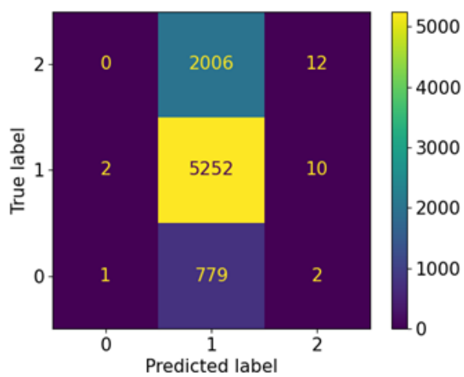


Fig 10. Confusion matrix for case 2 test dataset, with 7 hidden layers with 32, 64, 128, 256, 128, 64 and 32 neurons respectively

Outcome from Fig. 10: 68% accuracy was obtained on the training data, with a loss of about 0.7

Prediction Matrix	Description
Precision	0.34, 0.66, and 0.36 for short term, medium term and long term respectively



Outcome from Fig. 11: 68% accuracy was obtained on the training data, with a loss of about 0.7

Prediction Matrix	Description
Precision	0.52, 0.67, and 0.58 for short term, medium term and long term respectively
Recall	0.08, 0.96, 0.11, for short term, medium term and long term respectively
Proportion of each class in original dataset	25%, 65% and 0.1% for short term, medium term and long term respectively

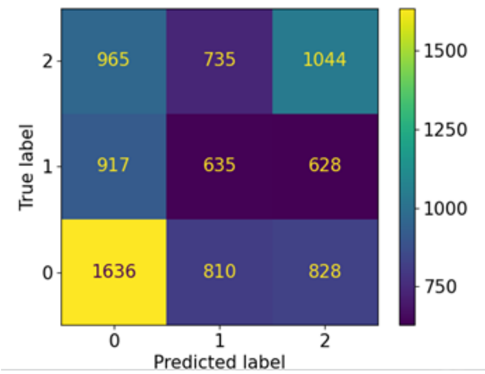


Fig 12. Confusion matrix for case 3 test dataset with 3 hidden layers of 32, 64, and 128 neurons respectively

Outcome from Fig. 12: 65% accuracy was obtained on the training data, with a loss of about 0.9.The accuracy on the training dataset was suboptimal and hence, no testing was performed on this dataset

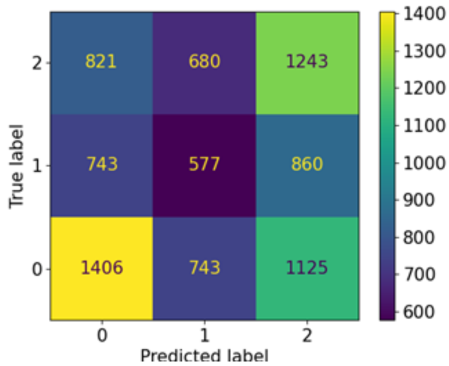


Fig 13. Confusion matrix for case 3 test dataset with 7 hidden layers of 32, 64, 128, 256, 128, 64 and 32 neurons respectively

Outcome from Fig. 13: 78% accuracy was obtained on the training data, with a loss of about 0.5

Prediction Matrix	Description
Precision	0.41, 0.30, and 0.45 for short term, medium term and long term respectively
Recall	0.34, 0.29, 0.52, for short term, medium term and long term respectively
Proportion of each class in original dataset	3%, 27% and 40% for short term, medium term and long term respectively

4.0. Discussion and Recommendations

The model development could have resulted in prediction efficiency if the data was collected keeping the projects' objective in mind. During the data wrangling stage, some observations were unrealistic as they had a very short duration for relatively long-span projects. Despite wrangling and cleaning, the assumptions evoked could not sufficiently produce the near-ideal dataset intended. Even with this challenge, the developed model performs quite well in some test cases, as seen in section 3.3. The model's accuracy on the training data set was observed to increase with a denser neural network. For very ambitious trials, an accuracy of about 90% was obtained on training data, even though performance on testing data was far less than 60%. This phenomenon was attributed to the possible overfitting of the training data. Thus, such models were eschewed, and regularization enabled a more accurate assessment of generalizability. The developed models were validated on some portions of the original dataset, and the results are attached in the appendix.

For the following steps, the authors propose to explore other techniques for improving the model to enhance generalizability. Since there is no consensus threshold that classifies project durations into the three labels chosen in this work, the authors believe that case 3 is the most realistic since it gives an almost equal chance for classifying a given observation into the derived classes, as seen from the confusion matrix plot in section 3.3. Additionally, the difficulties currently encountered in establishing appropriate thresholds to categorize observations as "short-term," "medium-term," or "long-term" could present a potential research opportunity: one of identifying which threshold produces the best/optimal classification results. This can be seen as a problem of parameter identification or inverse analysis to determine suitable thresholds for classifying the duration of road construction projects as "short-term", "medium-term", or "long-term", based on which of the trail thresholds yields the best predictive model. Finally, the key lesson learned is that the developed model is as good as the data. Therefore, experiments for scientific research must be planned in a way that effectively collects data concerning the project's stated hypothesis.

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Appendix

	variable	mean	min	median	max	nmissing
1	Symbol("Distance(mi)")	0.648688	0.0	0.20917	106.85	0
2	Symbol("Temperature(F)")	65.8212	-21.0	69.0	117.0	0
3	Symbol("Wind_Chill(F)")	64.987	-30.0	69.0	117.0	0
4	Symbol("Humidity(%)")	61.1661	4	63.0	100	0
5	Symbol("Pressure(in)")	29.0751	20.26	29.39	30.65	0
6	Symbol("Visibility(mi)")	9.46639	0.0	10.0	100.0	0
7	Symbol("Wind_Speed(mph)")	7.27306	0.0	7.0	38.0	0
8	Symbol("Precipitation(in)")	0.0027549	0.0	0.0	1.56	0
9	:Project_Duration_Days	198.71	50	173.0	2010	0
10	:Project_Duration_Class	nothing	"long term"	nothing	"short term"	0

Fig. 14: Summary of the cleaned dataset

Data before wrangling

Start_Time	End_Time	Distance(mi)
"4/5/2019 16:00"	"9/29/2020 11:53"	1.1035
"11/12/2021 7:59"	"11/12/2021 8:22"	0.433173
"10/12/2021 7:17"	"10/12/2021 9:18"	0.192266
"2/10/2021 2:46"	"2/17/2021 23:59"	0.0321121
"12/6/2021 7:50"	"12/6/2021 9:53"	0.141399
"9/30/2021 1:39"	"9/30/2021 3:40"	0.0732397
"9/16/2021 15:08"	"9/16/2021 15:40"	0.853305
"12/1/2021 8:51"	"12/1/2021 10:56"	0.226995
"7/31/2021 12:11"	"7/31/2021 13:06"	0.258762
"11/19/2021 14:06"	"11/19/2021 16:27"	0.130887
"7/22/2021 10:45"	"7/22/2021 11:31"	0.607945

Data after wrangling

Start_Date	End_Date	Project_Duration_Days
2019-04-05	2020-09-29	544
2021-11-12	2021-11-12	1
2021-10-12	2021-10-12	1
2021-02-10	2021-02-17	8
2021-12-06	2021-12-06	1
2021-09-30	2021-09-30	1
2021-09-16	2021-09-16	1
2021-12-01	2021-12-01	1
2021-07-31	2021-07-31	1
2021-11-19	2021-11-19	1
2021-07-22	2021-07-22	1

Fig. 15: Figure showing data set before and after data wrangling

Start_Lng	End_Lat	End_Lng	Distance(mi)	Start_Date	End_Date	Project_Duration_Days	Project_Duration_Class
-93.1524	32.8507	-93.1644	1.1035	2019-04-05	2020-09-29	544	"long term"
-83.2652	39.7261	-83.2465	1.10024	2020-04-20	2020-07-22	94	"short term"
-73.9652	40.763	-73.974	0.952071	2021-05-10	2021-12-10	215	"medium term"
-80.1912	26.1871	-80.1874	0.24557	2020-11-15	2021-12-30	411	"long term"
-87.724	41.8312	-87.7242	0.453084	2021-07-04	2021-10-08	97	"short term"
-86.4798	39.6149	-86.4798	0.601812	2021-03-10	2021-12-31	297	"medium term"
-112.063	33.5092	-112.066	0.173348	2021-02-27	2021-12-28	305	"long term"
-80.1906	25.8904	-80.1845	0.380199	2021-04-13	2021-12-13	245	"medium term"
-80.3374	25.7482	-80.3356	0.118257	2021-06-16	2021-12-14	182	"medium term"
-90.7869	42.44	-90.8007	0.701292	2021-05-14	2021-10-22	162	"medium term"
-92.4132	41.0376	-92.4158	0.999269	2020-07-20	2020-10-31	104	"medium term"

Fig. 16: Data set after adding project duration classification

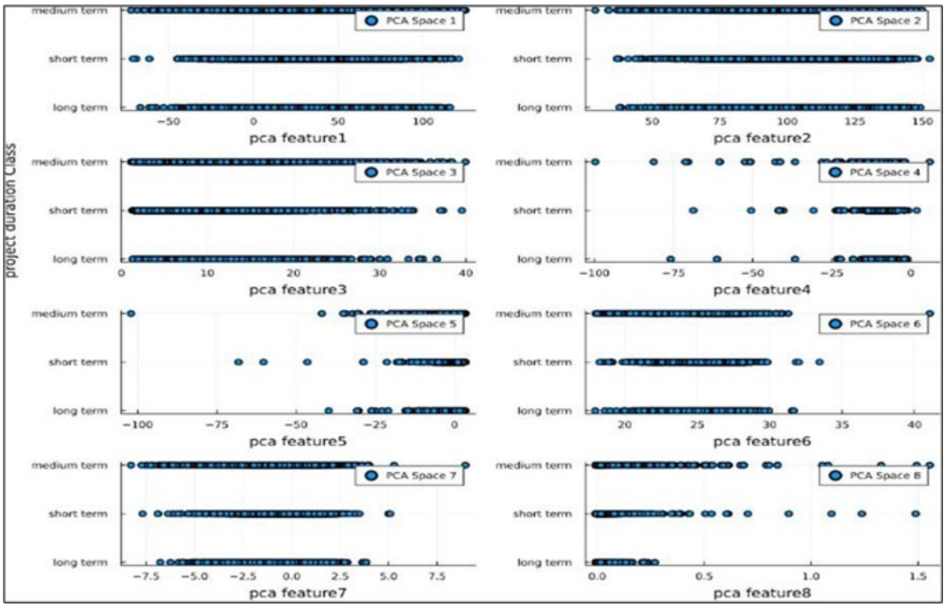

Fig. 17: Transformed data in PCA coordinate frame

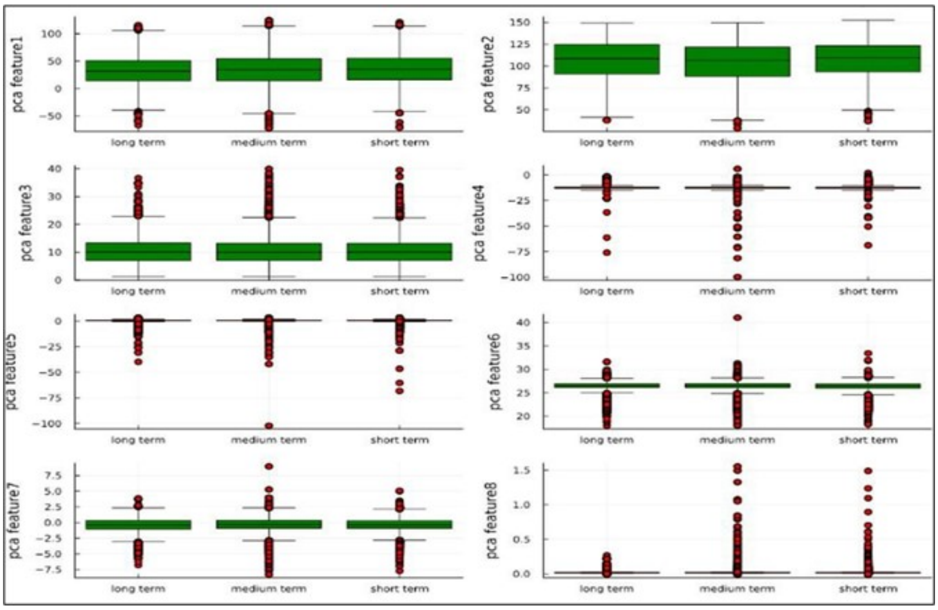

Fig. 18: Boxplots of transformed data in PCA coordinate frame

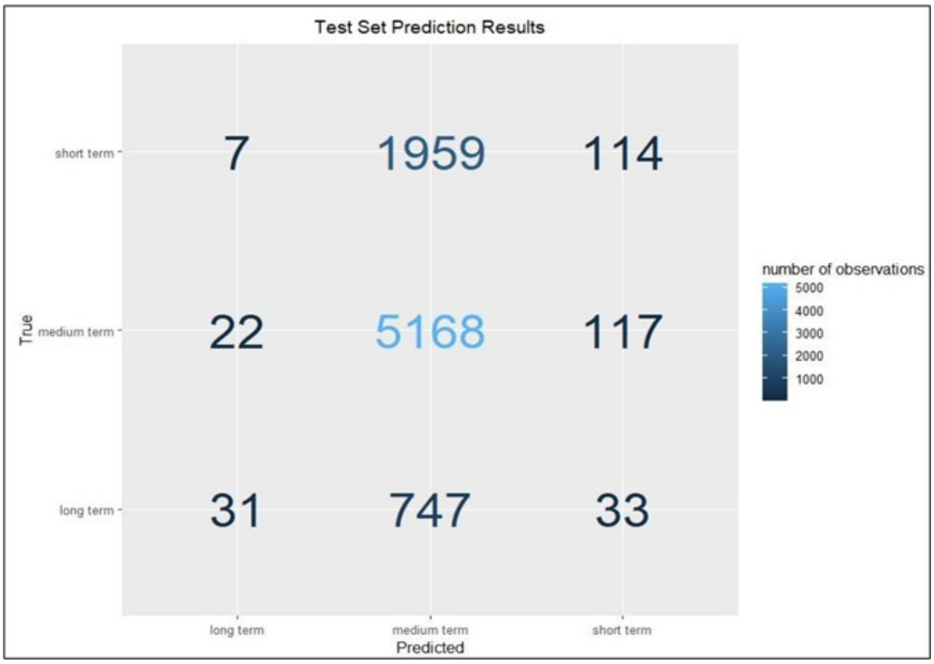

Fig. 19: Confusion matrix plots from R for case 2 test dataset, with 1 hidden layer of 32 neurons respectively

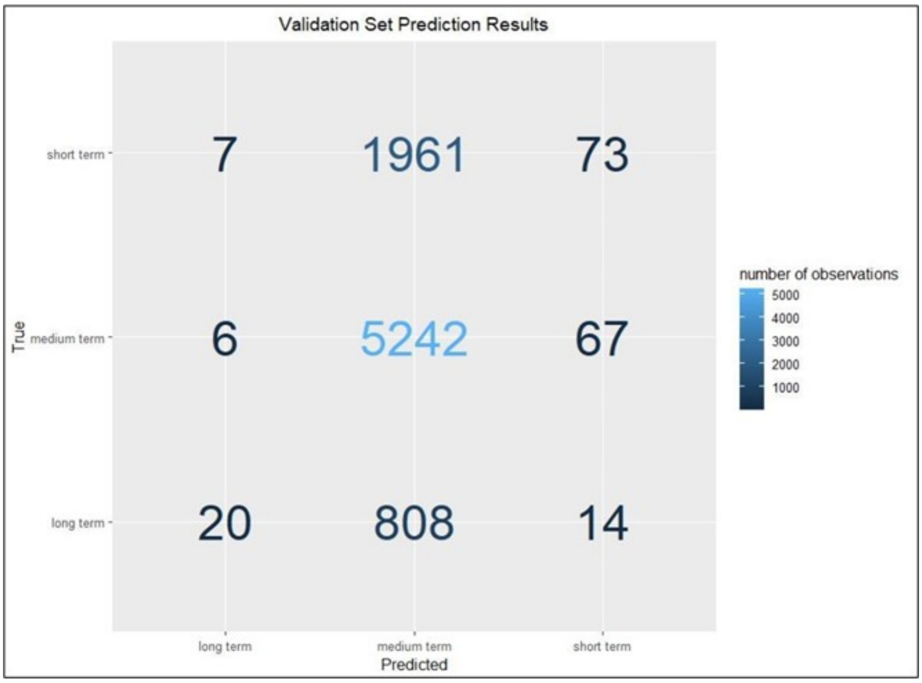

Fig. 20: Confusion matrix plots from R for case 2 validation dataset with 1 hidden layer of 32 neurons respectively