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Predicting Culvert Deterioration Using Physical and Environmental Time-Independent Variables

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PREDICTING CULVERT DETERIORATION USING PHYSICAL AND ENVIRONMENTAL TIME-INDEPENDENT VARIABLES

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ABSTRACT

Given a database of approximately 8,000 culverts in South Carolina with varying sizes, types, configurations, and the associated ratings of different output categories, a predictive deterioration model was produced in an attempt to match the ratings of these output categories. These models used the physical culvert information given in the database of culverts and associated environmental characteristics including historical temperature, precipitation, pH, and estimated runoff coefficient as inputs for the model. The models used combinations of inputs that produced the model with the best performance measures. In addition, a separate group of models was created for each of the six culvert types commonly found in South Carolina. These models used different combinations of the input variables to produce a model that rated a culvert in ten categories: cracking, separation, corrosion, alignment, scour, sedimentation, vegetation, erosion, blockage, and piping. The scores for each of these categories were combined to give an overall composite score for each of the culverts.

Two types of models were used for each of the culvert types and output categories, a logistic regression model and an artificial neural network model. The purpose of this model was to allow the user of the model to input a culvert or group of culverts and receive their expected culvert ratings in accordance with the *SCDOT Field Inventory and Inspections Guidelines*. The model also produced a composite rating, consisting of a combination of the ten input categories predicted by the model. There were several preset composite weights for these categories, but the model also adapted for a user input combination of output categories.

The models produced were shown to have a coefficient of determination of between 0.25 for poorly correlated models to a coefficient of determination 0.80 for better correlated models when comparing the predicted culvert score with the actual culvert score. The models that were produced were meant to serve as both a tool to determine the approximate health of a group of culverts, and to compare the scores of a group of culverts allowing the SCDOT to make decisions about rehabilitation and repair without physically inspecting a culvert.

DEDICATION

I would like to dedicate this work to my mother and father for their love, support, and patience throughout my education.

ACKNOWLEDGMENTS

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CHAPTER ONE

Introduction

Culverts can be defined as pipes which are typically located under a roadway and help to direct the flow of water. Culverts differ from bridges in that they are smaller and often hidden below the roadway. Because culverts are often concealed and can be difficult to access, their condition can be hard to determine through traditional inspection techniques. In South Carolina alone, there are tens of thousands of culverts that were installed over 50 years ago and are in varying states of deterioration (SCFOR 2015). With such a large infrastructure of culverts, it is important to be able to prioritize the repair and rehabilitation efforts. The failure mechanisms of culverts can vary extensively, and the condition of a culvert can be the combination of many different criteria. In addition, there are many factors that affect the condition of a culvert that include both physical and environmental characteristics. The behavior of a culvert is largely effected by its material type. In South Carolina, six primary types of culverts are used: reinforced concrete pipe (RCP), corrugated metal pipe (CMP), corrugated aluminum pipe (CAP), high density polyethylene pipe (HDPE), masonry pipe, and culverts classified as mixed or other culverts. Of these six types of culverts, RCP culverts are by far the most common in the state of South Carolina. The combination of these characteristics and their relationship with the condition of the culvert is complex in nature.

Previous researchers have used Markov models as well as multiple discriminant analysis (MDA) to predict the structural deterioration of culverts. This study will focus primarily on creating multinomial logistic regression (MLR) and artificial neural network (ANN) models that can be used to predict the condition of a culvert without on-site investigations or assessments. These models will serve to predict a variety of output characteristics for each culvert as well as provide different models for each culvert type. The output predicted by the model will be combined using a weighted average of these output categories. These weights can be determined by the model's user or by previous data collected from various state Departments of Transportation and attempt to give the user an idea of the overall health of a culvert as well as the variability that exists within the model's output prediction. The goal of these models is to give an estimate of a culvert's state of deterioration using physical and environmental characteristics that allow the user to prioritize those culverts that need further assessment and ultimately repair and replacement.

CHAPTER TWO

Objectives

The primary objective of this study was to create and verify a model that could be used to predict the condition of culverts in South Carolina. This model was based on a database of historical data that was used to pair a culvert's physical and environmental characteristics with the condition assessment of the culvert. Two different model type were used to probabilistically predict a set of inspection criteria in an attempt to maximize the efficiency of the repair and assessment techniques. The multinomial logistic regression (MLR) and artificial neural network (ANN) models attempted to predict the condition all six culvert types and all required assessment variables defined by the *SCDOT Field Inventory and Inspections Guidelines*.

The probabilistic model was not a deterioration model, because a time-dependent variable associated with each culvert was absent from the database of culvert information. Using other physical and environmental parameters in combination with physical characteristics associated with each culvert, the model was used to identify the effects of these parameters and determine a culvert overall condition. The accurate mapping and assignment of the site specific parameters not included in the database of information was also an important objective in this study. In addition to creating the two models, regression techniques were used to post-process the output produced by these models in an effort to correct for any present bias and quantify the variability that exists in the population of culverts in South Carolina. The neural network models were also dependent on several factors including the number of neurons in each layer, the training algorithms used to create the network, and the combinations of input variables. These variants were manipulated to give the most accurate neural network model. The final models will allow the user to determine the output rating of any of the criteria used in the SCDOT *Field Inventory and Inspection Guidelines* as well as determine a composite score for each of the culverts. Using regression analysis, a final composite score would be calculated and the standard deviation would be presented. These efforts were made in order to accurately identify the culverts in South Carolina in need of assessment or repair without performing any physical testing or on-site investigation.

CHAPTER THREE

Literature Review

Researchers have created many models that predict the deterioration of culverts across the United States. Some of these models focus on the overall structural deterioration, while others focus on one or more aspects of the deterioration such as corrosion or scour. In addition, many of the models utilize different sets of input variables and implement different statistical models to predict the condition of culverts to different levels of effectiveness.

Model Types

There have been several types of statistical models that are used to determine deterioration in complex infrastructure systems. Some simple are single parameter fitted distributions typically using age as the primarily independent variable (Verma et al 2013). Other models employ the Markov models which utilizes rates of deterioration in terms of the probability of changing condition state or transitional probabilities (Baik et al. 2006). Most often, both the fitted distribution models and Markov deterioration models have single variable inputs. In the case where more information on the physical or environmental characteristics exist, multi-variable probability models are suitable for the prediction of various output criteria. The most applicable multi-variable models for this study are neural network models and logistic regression models.

Neural Networks

Neural network models are based on three distinct functional operations that determine the output given a vector of inputs. In the case where there is only one input, the first of these functions is a weighting function in which an input is multiplied by a scalar weight. The second function adds a scalar bias term to the scalar weight and scalar input multiplication. Finally, a transfer function is used to produce a scalar output, shown in **Figure 3.1** as a simple neuron (MATLAB 2015a). There are three choices for the transfer function using the MATLAB 2015a Neural Network Toolbox, a log-sigmoid function, a tan-sigmoid function, and a linear transfer function. Often, the sigmoid transfer functions are used in problems with pattern recognition applications, while the linear transfer function is used in function fitting applications.

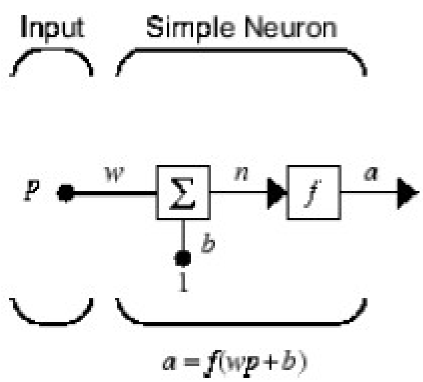


Figure 3.1: Layout of Simple Neuron

For culvert deterioration models, there a several input variables that are used, so the scalar inputs and weighting functions become vectors that are added to a bias term used in a transfer function producing a scalar output (**Figure 3.2**). The network can become more complex as multiple neurons can be used in a single layer. These neurons now produce a vector of outputs and the weighting functions become a matrix. Finally, multiple layers can be used in a neural network to create networks that can approximate complex relationships between multiple inputs and outputs (**Figure 3.3**).

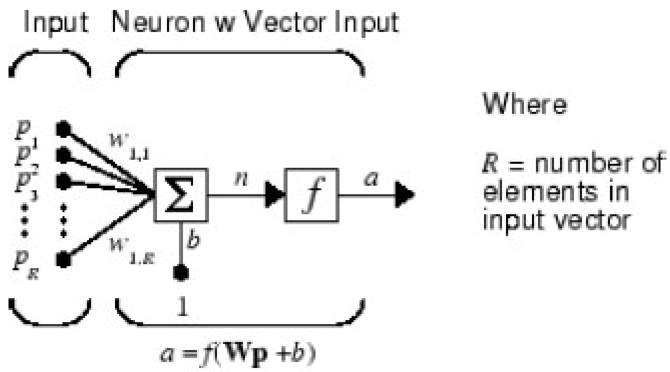


Figure 3.2: Combination of Multiple Inputs in a Simple Neuron

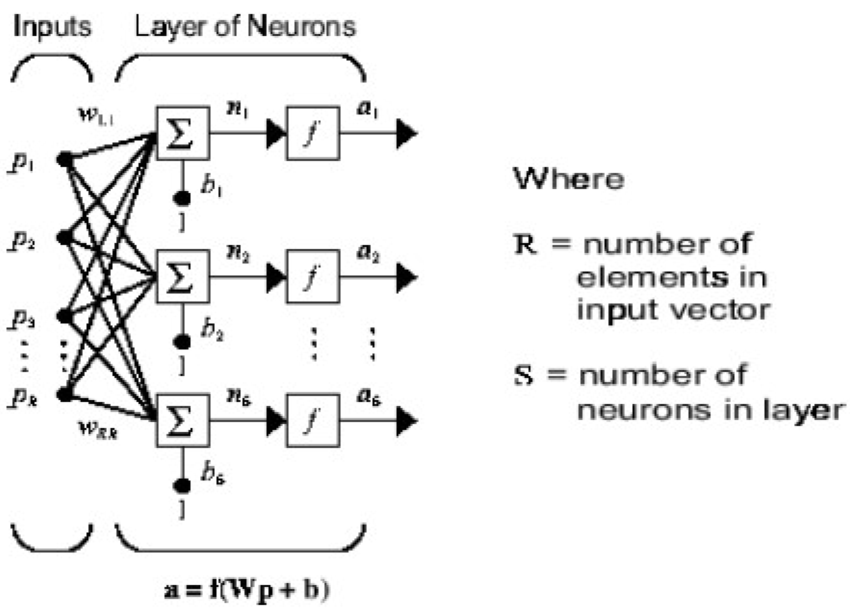


Figure 3.3: Multiple Inputs Producing Multiple Outputs in Complex Neurons

Previous neural network models used to predict the condition of storm-water pipes used three layers of neurons with the number of neurons. These three layers correspond the number of inputs, the number of patterns in the total number of output options, and finally the number of output options respectively (Tran et al. 2009). The number of neurons in the second layer, associated with the number of patterns in the output options, are also known as hidden neurons. Determining the number of neurons to use can cause problems of overfitting or underfitting. Ultimately the convergence principle was applied to achieve the most accurate results when neural networks are used (Sheela and Deepa 2013). In addition, the amount of data that is used to train and validate the neural network model can have an impact on the accuracy of the model. It is common to use the mean-square error to determine the accuracy of the model and select the best model based on the least error (Tatari et al. 2013).

Besides the construction of the network, the parameters used to train the network have an impact of the final model. Previous research has used 80% of the data to train the network and 20% of the data to test the network (Tatari et al. 2013) or 75% for training and 25% for testing (Ariaratnam et al. 2001). MATLAB's built-in Neural Network Toolbox uses a default setting of 70% of the data to train the network, 15% of the data to validate the network, and 15% of the data to test the network. The validation checks are defined as the number of iterations performed during which the performance function of the neural network fails to decrease. The primary training algorithm used to train the neural network is called the Levenberg-Marquardt method. This method is especially adept at solving nonlinear problems with multiple inputs and utilizes two minimization techniques: the gradient descent method and the Gauss-Newton method. (Marquardt 1963). These two methods are used based on the scalar value of the update parameter, λ. When values of λ are large, the Gauss-Newton method is used to determine λ, and when λ values are relatively small, the gradient descent method is used to calculate

λ. Based on previous research, the Levenberg-Marquardt method for training neural networks has proven to be both accurate and computationally manageable for similar types of problems (Aimin et al. 2011).

Logistic Regressions

Logistic regression models give another option in efforts to solve complex problems with multiple inputs. Common types of logistic regressions include linear regressions and logistic regressions. Linear regressions can be used to determine the relative probability of a desired output as the linear addition of the input variables, (X_1, X_2, … , X_n) and a weighting factor (β_1, β_2, … , β_n). The logarithmic logistic regression uses the same principles as a linear logistic regression but incorporates the logarithmic function (Eqn. 3.2).

$$\ln\frac{P(\text{Output}=1)}{P(\text{Output}=0)}=\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_nX_n \qquad \text{(Eq 3.1)}$$

Furthermore, the logistic regression model can be broken down into binary and multinomial logistic regression. Binary logistic regressions predict the probability of an event that is binary (it either occurs or does not), while multinomial logistic regression allows for a larger breakdown in the output of the model. In the case of predicting a rating of a culvert, the logistic regression can predict the relative likelihood of a specific output score being less than or equal to the threshold value (Eq 3.3). The value of *k* in Equation 3.3 varies from the lowest possible score to one value less than the highest possible score. These output scores need to be integer values for the log-likelihood algorithm to create a best-fit model.

$$\ln \frac{P(\text{Output} \leq k)}{P(\text{Output} > k)} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_n X_n \qquad \text{(Eq 3.2)}$$

Multinomial logistic regression is applicable when the output is a scaled rating of the desired variable. In the case of culvert deterioration multinomial logistic regressions, this allows for the output variables to be an integer scaling.

Results of Regression and Neural Network Models

Logistic regression models have been created with varying degrees of success. Because the primary performance objectives can change between different models, it can be difficult to compare the results of various models. For linear regressions, a coefficient of determination of 0.823 was achieved using various combinations of input variables relying primarily on age and pH (J., Colorado 2014). Other models reported their accuracy as a percent of culverts correctly identified in each condition state. The logistic regression model produced an overall accuracy of 68.7% with 83.1% percent of culverts in need of repair being correctly identified (Salem). A neural network model created in 2006 achieved similar results with a 71.5% success rate in the calibration set and a 66.9% success rate in the validation set (Tran et al. 2006). Using 39 culverts in Ohio, a neural network was created that proved to be 100% successful in identifying culverts in need of inspection; however, it must be noted that when a given data set had less than three data points, the accuracy could not be tested (Tatari et al 2013). Furthermore, a model created to predict restrain in culverts achieved a coefficient of determination of greater than 0.95 when comparing the predicted output versus the actual output (Al-Gburi et al 2015).

Model Performance Measures

Multinomial logistic regressions can be verified using several methods. Like neural networks, the mean-squared error term can be an indication of the accuracy of the model. Another way of verifying logistic regressions and neural networks is through receiver operating characteristic (ROC) curves. These curves are a plot of the ratio of true positive data predicted against the ratio of false positive that are predicted. The threshold dividing positive and negative data is varied to achieve a curve that ranges from 0 to 1 on both the x and y axis (**Figure 3.4**). The measure of accuracy is the area beneath the curve and can range from 0.5 to 1.0. A ROC curve with an area under the curve of 1.0 perfectly separates positive and negative responses while an area under the curve of 0.5 or less is caused by a model that is as effective as randomly determining the positive and negative responses of each data point (**Figure 3.5**). While ROC curves are a good way of measuring the models ability to separate data, they only are applicable for binary logistic regression models. They can be applied to multinomial logistic regressions and neural networks with more than one possible output on a term by term basis be creating a curve that represents each possible output.

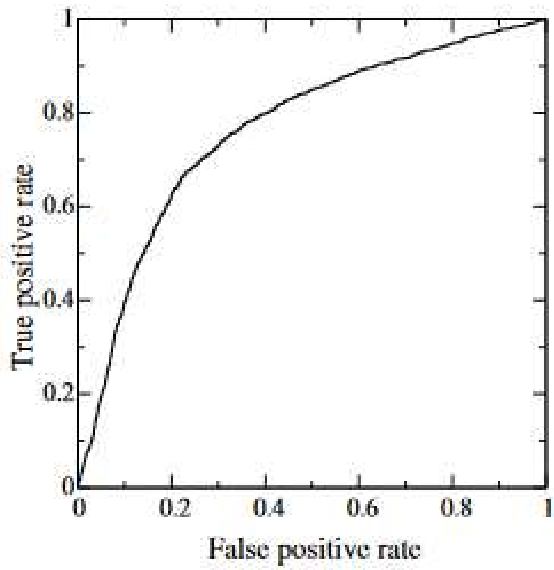


Figure 3.4: Sample ROC Curve (Fawcett 2006)

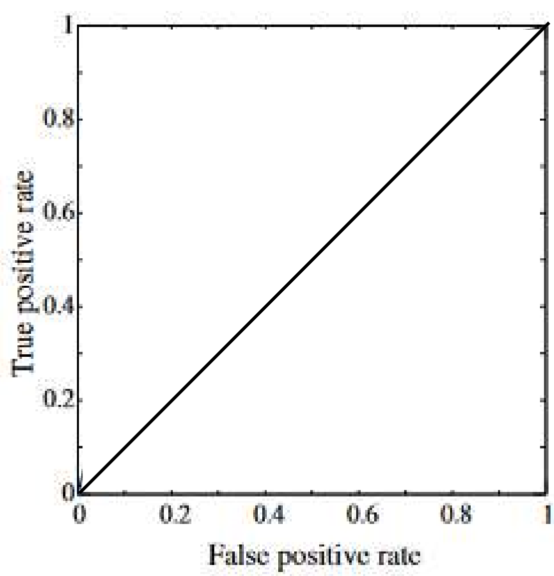


Figure 3.5: ROC Curve Showing Model with no Prediction Power

Using ROC curves to validate the logistic regression models and neural network models also allows the user to determine the amount of false positives and true positives are to be expected at a given threshold level (Fawcett 2006). By changing the threshold values appropriately, a model can be created that may capture more of the false positives at the expense of identifying all true positives. Typically, the threshold value is set by the output of the maximum log-likelihood function.

Another popular and simpler technique for determining the accuracy and performance of a model is the coefficient of determination between the predicted data set and the observed data set. When the coefficient of determination is high, it means the model can minimize the error of each culvert's predicted output and the observed output. While this measure may be a good thing in some cases where a very accurate prediction of the output is required, it may prioritize fitting the majority of the data at the expense of the outliers. In the case of culvert deterioration, these outliers often indicate the culverts in most need of assessment and repair. The error term can be expressed by Eq. 3.4 and provides the user with a model that can increase a model's accuracy and robustness in comparison to a typical least-square regression (*Monographs on Statistic and Applied Probability*). In this equation the output becomes a fit of the relationship between the model output and observed output including the error term.

$$y = Ax + b + \varepsilon \qquad \text{(Eq 3.3)}$$

Input Variables

The variety and number of input variables used in previous culvert prediction models vary depending on the type of culvert and desired output variables. In all studies summarized in **Table 3.1**, age was considered to be an important factor in the deterioration and condition estimation models. In order to be considered a deterioration model, one or more of the input variables must be considered time-dependent. The other main physical characteristics that were used in most models were the culverts size (most often diameter) and slope. Of the other previous deterioration models, the physical culvert characteristics that were used to predict culvert health were depth of cover over the culvert, culvert protection (for metal culverts), and thickness of the culvert. In addition to the physical culvert characteristics, several site specific environmental characteristics were considered to be significant. The most commonly used environmental characteristics included the soil abrasion characteristics, the water pH, and flow characteristics of the water source.

Table 3.1: Distribution of Relevant Input Variables

REFERENCE	Tran et al. 2009	Meegoda and Juliano 2009	Wyant 2002	Urrea 2014	Thompson et al. 2012	Ariaratnam et al. 2001	Ana and Bauwens 2009	Najifi & Kulandaivel 2005	Micevski et al. 2002
Age	X	X	X	X	X	X	X	X	X
Thickness	X			X					
Size	X	X		X	X	X	X	X	X
Depth	X						X	X	
Slope	X	X		X	X		X	X	
Tree Count	X						X		
Hydraulic Conditions	X								
Exposure	X								X
Soil Abrasion	X		X	X	X		X		X
Thornweite Moisture Index	X								
pH			X	X	X				
Flow Parameters				X	X		X		
Flooding Potential					X				
Traffic Load							X		
Culvert Protection Type		X			X				

These variables were found to have varying effects on the deterioration model. Because most of the input variables (outside of age) are time-independent, their effect on the deterioration curves can range from heavily to not at all depending of the other available data, culvert type and failure modes.

While a large range of input variables may allow for a broader logistic regression model, there are several assumptions that govern the use of input variables in a logistic regression. Theoretically accurate logistic regressions assume neither underfitting nor overfitting, that is all necessary input variables are used in the model's creation and no unnecessary input variables are used. In the case of culvert deterioration, it is not possible to include all input variables, but it is equally important to exclude variables that have no impact on a culvert's condition. To determine whether a given input variable has an effect on the model's ability to accurately predict a culvert's condition previous research has used the Wald statistic and the likelihood-ratio test to determine a given input variables effect on the model (Ariaratnam et al. 2001). The Wald statistic is the square of the z-statistic when comparing the coefficient of the input variable, β, to 0. As the statistic approaches 0, the influence of the input on the model reduces. The likelihood-ratio test compares the ratio of the outputs from the likelihood function for a model with and without the input variable. As the ratio approaches zero, the importance of the input variable increases. Another important assumption of logistic regressions is the lack of multicollinearity, or that all input variables are statistically independent. This assumption can be checked by determining the correlation coefficients for any two input variables.

The assumptions of logistic regressions that apply to input variables are not necessarily required for neural networks. In order to allow for the best comparison between model types it is advisable to use the same input variable criteria to evaluate the inputs of neural networks as logistic regressions.

Output Variables

Many deterioration models are used to predict a single output rating. This rating can be defined in many ways including the probability of failure, the overall assessment condition, or remaining service life. Some deterioration models differentiate structural performance from hydraulic performance in the output of the models (Beaver et al. 2004). There are not many existing models that use the variety of the input variables to predict the failure modes or causes of deterioration like cracking, joint misalignment, and corrosion. A summary of the value given to the predicted output variable for culvert models is shown in **Table 3.2.**

Table 3.2: Summary of Output Variables Predicted in Culvert Models

REFERENCE	Verma et al. 2013	Meegoda et al. 2004	Beaver et al. 2004	Kleiner et al. 2006	Kleiner & Rajani 2001	Micevski et al. 2002	Ariaratnam et al. 2001	Najifi & Kulandaivel 2005	Tran et al. 2009	Ana and Bauwens 2009	Salem et al. 2012	Tatari et al. 2013
Remaining Service Life	X	X										
Structural Performance			X			X						
Hydraulic Performance			X									
Probaility of Failure				X	X					X	X	
Cracking of Pipe							X					
Overall "Condition"								X	X			X

While the deterioration models do not predict the various causes of deterioration individually, most culvert assessment and management practices measure these conditions. The deterioration causes that were measured most frequently in culvert assessment strategies were culvert cracking, joint separation or damage, and corrosion with a total summary shown in **Table 3.3**. The *SCDOT Field Inventory and Inspections*

Guidelines requires the inspection and rating of culvert cracking, separation, corrosion, alignment, sedimentation, scour, vegetation, erosion, blockage, and piping. All of the desired assessment variables play a role in a culverts overall condition, deterioration state, and need for repair.

Table 3.3: Distribution of Assessment Categories Used to Describe Culverts

REFERENCE	SCDOT Culvert Inspection Guide	Wyant 2002	Ariaratnam et al. 2001	Yang & Allouche 2009
Cracking	X	X	X	X
Joint Separation	X	X	X	X
Corrosion	X	X	X	X
Alignment	X			X
Scour	X			X
Sedimentation	X			
Vegetation	X			
Erosion	X	X		X
Blockage	X			X
Piping	X			X
Hydraulic Capacity		X		
Deflection		X	X	X
Spalls				X
Delamination				X
Abrasion				X

Conclusion

There exists a great diversity of models used to predict the deterioration or condition state of culverts. The most applicable multi-variable models for this study are neural network models and logistic regression models. Both of these types of models can be successful in determining the relationships between multiple inputs and a single output. In addition to the type of model used to predict a culvert's condition, the number of input variables and their relevance can play a large role in the accuracy of the final model. Determining which input variables are important to the model is essential in creating a model that does not overfit or underfit the desired output. Most often the desired output is a single indicator of the culvert's overall condition; however, this indicator is often a combination of many failure modes or conditions. The successful combination of the essential input variables into models that accurately predict the deterioration characteristics that describe the state of a culvert will produce the most useful model for the desired objectives.

CHAPTER FOUR

SCDOT Culvert Database

Database Inventory and Assessment Information

The information that was provided by the South Carolina Department of Transportation followed the format of the *SCDOT Pipe & Culvert Field Inventory and Inspection Guidelines*. This document outlined the information that was required during field assessments as well as the scale for which these assessment categories are to be measured. The database of information was split into two sections, culvert inventory and culvert assessment. The culvert inventory included information shown in **Table 4.1**. These characteristics largely describe the physical properties of the culverts in South Carolina. Important characteristics from the inventory database include Culvert ID and Number, Culvert Type, culvert dimensions, and latitude and longitude coordinates. The culvert assessment database contained all the information in regards to an assessment of the culverts listed in the culvert inventory. The categories provided in the assessment database is shown in **Table 4.2**. The culverts were mapped to a specific assessment input through the associated culvert ID number.

Table 4.1: Inventory Information provided by *SCDOT Pipe & Culvert Field Inventory and Inspection Guidelines*

Inventory Information	
District	Liner Diameter
County	Liner Width
Route Type	Liner Height
Route Num	Liner Notes
AUX	Inlet Pipe End Type
Beg MP	Inlet End Treatment
End MP	Inlet Apron Type
Culvert ID	Outlet Pipe End Type
Culvert Num	Outlet End Treatment
Num Barrells	Outlet Apron Type
Culvert Type	Date Inventoried
Culvert Shape	Inventoried By
Diameter	Date Modified
Width	Modified By
Height	**Lat**
Length	**Long**
Liner Type	Geo Accuracy

The information from the assessment criteria outlined in the *SCDOT Pipe & Culvert Field Inventory and Inspection Guidelines* was meant to address three main areas of each culvert, the inlet, the outlet, and the culvert barrel (**Figure 4.1**). In total, 35 assessment categories were ranked in order to give a condition of the culvert. A total of 13 categories addressed the inlet, another 13 addressed the outlet, 7 addressed the barrel condition, and 2 addressed the condition of the channel.

Table 4.2: Assessment Information provided by *SCDOT Pipe & Culvert Field Inventory and Inspection Guidelines*

Assessment Information		
Culvert ID	Inlet End Section Separation	Outlet End Section Blockage
Channel Alignment	Inlet End Section Scour	Outlet End Section Corrosion
Channel Scour	Inlet End Section Vegetation	Barrel Corrosion
Channel Sediment	Inlet End Section Blockage	Barrel Cracked
Channel Vegetation	Inlet End Section Corrosion	Barrel Alignment
Channel Erosion	Oulet Headwall (Y/N)	Barrel Sedimentation
Outlet Channel Alignment	Oulet Headwall Cracked	Barrel Joint Separation
Outlet Channel Erosion	Oulet Headwall Separatation	Barrel Piping
Inlet Headwall (Y/N)	Oulet Headwall Sour	Barrel Blockage
Inlet Headwall Cracked	Outlet Apron (Y/N)	
Inlet Headwall Separation	Outlet Apron Cracked	
Inlet Headwall Scour	Outlet Apron Separation	
Inlet Apron (Y/N)	Outlet Apron Scour	
Inlet Apron Cracked	Outlet End Section Cracked	
Inlet Apron Separation	Outlet End Section Separation	
Inlet Apron Scour	Outlet End Section Scour	
Inlet End Section Cracked	Outlet End Section Vegetation	

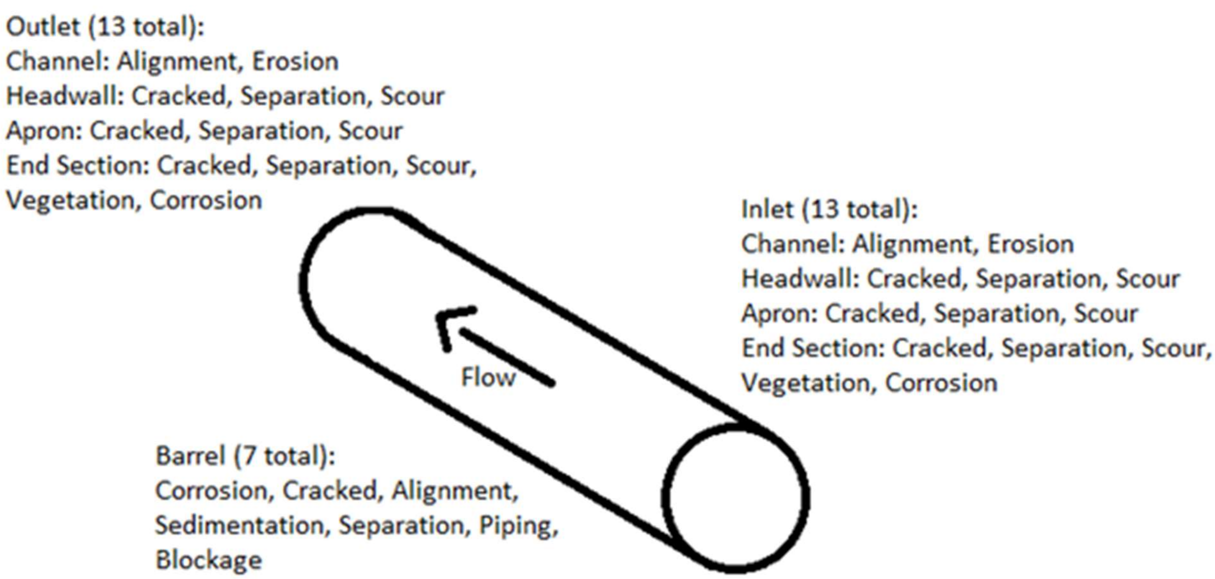


Figure 4.1: Distribution of the Variables Addressed in the *SCDOT Pipe & Culvert Field Inventory and Inspection Guidelines*

SCDOT Culvert Inspection Explanations

Each of the assessment ratings were assigned a condition state between 1 (worst condition) and 5 (best condition). The 35 assessment categories were subdivided based on the defect that they described. In total, 10 categories of defects or condition states were addressed by the culvert assessment. For each of these condition states, the *SCDOT Pipe & Culvert Field Inventory and Inspection Guidelines* gave clear indication to the definition of each condition states 1-5. The summary of these guidelines are shown below. The total number of assessment values that are related to the category are shown in parenthesis.

CRACKING (7)

1. Cracks greater than 1”, exposed rebar and extensive spalling of concrete surface
2. Large cracks are evident greater than 1/4”, extensive cracking, exposed rebar
3. Some cracks in excess of 1/8” efflorescence is evident; some rust streaks may be evident
4. Some minor cracking less than 1/8”
5. No cracks in structure

SEPARATION (7)

1. Total separation in excess of 3”
2. Major separation in excess of 1 1/2"
3. Medium separation less than 1/2"
4. Minor separation less than 1/8”
5. No separation between barrel and/or structure

CORROSION (3)

1. Large areas of material are missing, complete deterioration, full or partial collapse has occurred
2. Extensive perforations due to corrosion
3. Extensive corrosion, heavy pitting and some perforations of the material
4. Moderate to fairly heavy corrosion and/or deep pitting but very little to no thinning of material
5. Appears new or very close to new. There may be some minor pitting, slight corrosion

ALIGNMENT (3)

1. Channel is parallel to road or undermining embankment or road.
2. Channel and culvert are greater than 45 Degrees misaligned.
3. Channel and culvert are greater than 15 degrees and less than 45 Degrees misaligned
4. Channel and culvert are within plus or minus 15 Degrees alignment.
5. Channel and culvert are aligned.

SCOUR (6)

1. Scour or erosion at base of structure extending underneath structure in excess of 24".
2. Scour or erosion at base of structure extending underneath structure up to 24".
3. Scour or erosion at base of structure extending underneath structure up to 12".
4. Minor scour or erosion at base of structure but not extending under structure.

5. No undermining or scour.

SEDIMENTATION (1)

1. Sediment is greater than 75% of the area of the barrel.
2. Sediment is greater than 50% of the area of the barrel.
3. Sediment is greater than 25% of the area of the barrel.
4. There is sediment but less than 25% of the area of the barrel.
5. There is no sediment.

VEGETATION (2)

1. Vegetation severely blocking the inlet or outlet
2. Heavy vegetation at inlet or outlet impeding flow and gathering other debris.
3. Some vegetation at inlet or outlet, potential to impede flow.
4. A little vegetation at inlet or outlet no impediment to flow.
5. No vegetation at inlet or outlet.

EROSION (2)

1. Erosion threatening roadway.
2. Heavy erosion to stream bank or fill.
3. Moderate erosion to stream bank or fill.
4. Some erosion to stream bank or fill.
5. No erosion evident.

BLOCKAGE (3)

1. Totally blocked no flow culvert acting as a dam
2. Debris blocking flow. Water backing up due to blockage

3. Debris blocking flow little or moderate water back up
4. Some debris blocking flow.
5. There is no Blockage.

PIPING (1)

1. The majority of flow is occurring outside of the barrel.
2. Some of the flow is occurring outside of barrel.
3. Some water appears to be seeping around outside of barrel.
4. Piping may be occurring.
5. No piping is occurring.

An important assumption that was made was the linear relationship of the output scale for each of the categories. If this assumption was not made, the predictive models would need to predict an integer value for each of the scales. With this assumption, a continuous output scale can be used allowing for the prediction of ratings between each of the integer values. This means that the threshold for the assignment of these categories can be manipulated to correct the models over prediction or under prediction. Using logistic regressions, this value is still bounded by a lower bound of 1.0 and an upper bound of 5.0; however, an artificial neural network model can produce models with values above and below those bounds which were corrected using post processing. Once the model has predicted a value for each of the output categories and these predictions are combined into a single output variable, the model is corrected using a linear regression technique. Once the regression technique is applied, neither the logistic regression nor the artificial neural network are bounded by the lower limit of 1.0 or the upper limit of

5.0, though the models should not predict an output of significantly more or less than the prescribed limits.

Combining Outputs in Culvert Inspection Guide

A predictive model's ability to accurately determine the condition of a culvert is dependent on the amount of available and meaningful data and the desired assessment condition that is desired. For most culvert condition models, a single output is the product of the model. Given the various condition states that have been predicted and the variety in severity between the 10 condition states, a separate model would be used to predict each of these categories. For example, a culvert that has received an outlet end section vegetation rating of 2 may not be as critical as a culvert with a barrel corrosion rating of 2. By creating more models that are used to predict the well-defined assessment variables, the relationships between input variables and output variables can be linked with different condition states (**Figure 4.2**).

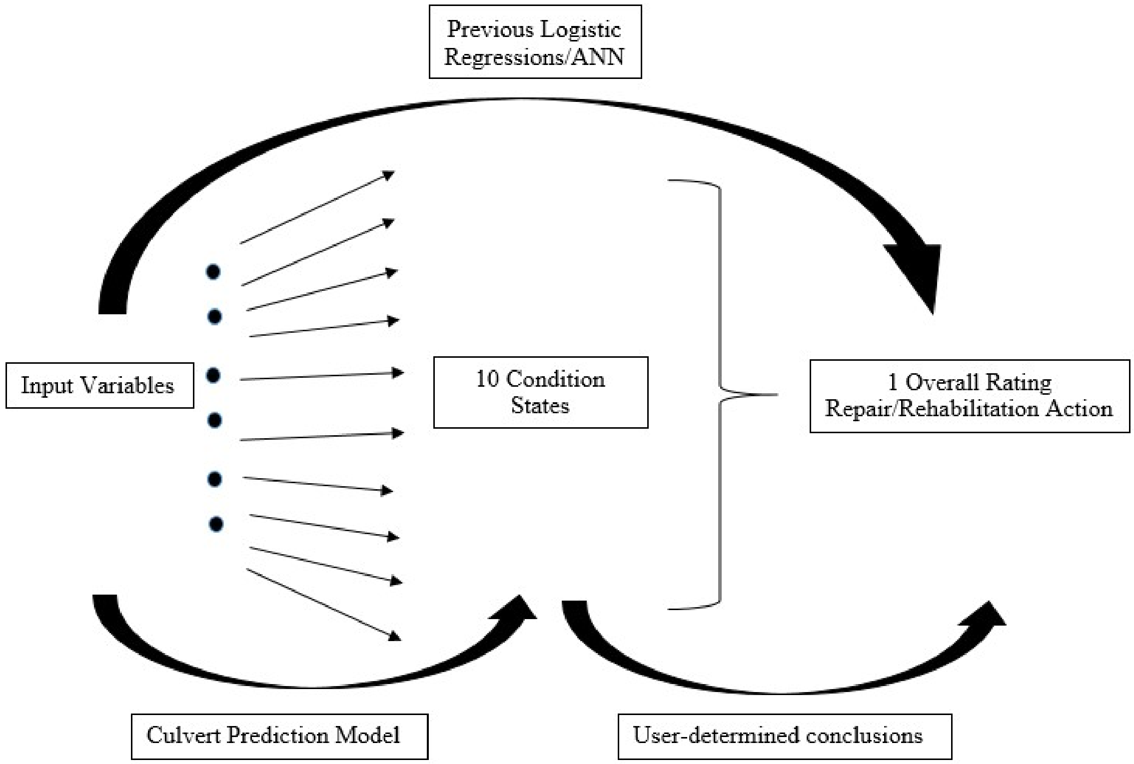


Figure 4.2: Conceptual Reasoning for Separate Output Models

In order to create as many diverse models as possible, while still presenting unique and meaningful models, the 35 assessment categories were combined into the 10 categories listed previously. Two methods for combining this information were originally used. The first method used the average values of the assessment variables to determine an overall rating for each of the ten categories. Because it is especially important for the predictive model to capture the culverts in poor condition, the second method used the minimum value of the assessment variables that make up each category. This method was ultimately used in the creation of the models as it served to capture the worst state of the culvert. For example, a culvert's inlet cracking rating could be a 5 (no cracking), while its outlet cracking rating could be a 1 (severe cracking). It is unlikely that a predictive model could determine the difference in the culvert inlet and outlet condition. It was most advantageous to attempt to predict the minimum value as it served to emphasize the culverts in most need of rehabilitation.

After inspection of the database of assessment information, it became apparent that the same assessment guide was used for all culvert types. Because the deterioration of each culvert varies significantly, rating a culvert on all of the possible output categories would not be necessary. For example, cracking is not to be expected in corrugated metal pipe (CMP) culverts just as corrosion is not likely to be visible in reinforced concrete pipe (RCP) culverts. Despite this fact, there was information in the culvert database for each of the culvert types and output categories. Understanding that some of this information may be useless, a model was created for each of the output categories regardless of the culvert type. It then became important for the user of the model to determine which output categories would be considered useful and which output categories would not apply to a specific type of culverts.

SCDOT Culvert Database Statistics

While the culvert inspection guide is fairly exhaustive in its ability to describe the condition of the culvert, the database does not require a complete entry for a given assessment log. That is, the inventory and the assessment of the culvert do not need to be entirely completed. A total of 5,196 or 58% of all culverts contained all of the necessary information including culvert ID, culvert number with matching assessment, culvert type, and valid latitude and longitude. Another advantage of using different models to predict each of the 10 condition states is that is allows for incomplete assessment information. Some culverts only had a few assessment areas complete. For example, this process allowed for some of the culverts to be rated in an output of cracked without having data on erosion, broadening the database of culverts. In total 5,181 culverts were able to be used in the creation of a predictive model.

The pre-processing of the SCDOT culvert database resulted in a matrix of culvert information where culverts without information on the type of culvert, a matching assessment for a culvert inventory ID, and valid latitude and longitude were removed. The distribution of culverts was observed after the pre-processing was complete. Some of the statistics regarding the distribution of culvert types is shown in **Table 4.3.** This distribution is important as the ability of both the logistic regression and the artificial neural network to accurately fit their parameters is based on the size and variability in the data set. For example, the accuracy of the models predicting the outputs of CAP and HDPE culverts may be significantly skewed as there are fewer than 20 culverts used to predict each output. The effect of the lack of data may appear to be both positive and negative as fewer culverts may allow for a predictive model to easily separate the data into categories without capturing the true meaning of the data.

Table 4.3: Distribution of Culvert Types in SCDOT Database

Type	RCP	CMP	CAP	HDPE	Masonry	Mixed/Other
Total	4059	193	17	14	634	264
Percent	78.34%	3.73%	0.33%	0.27%	12.24%	5.10%

It was important to recognize and catalog these trends in the original culvert database as it would allow for easier interpretation of the results once the models were derived. In addition to the disparity among culvert types, the ratings for each of the output categories were significantly skewed towards the higher rated culverts. **Table 4.4** shows the average rating for each of the culvert types and each of the culvert output categories. With such a large portion of the data rated at 4 and 5, any model's ability to define relationships between the input variables and a culvert in poor health become difficult to determine and a bias towards the higher rated culverts may exist.

Table 4.4: Average Rating for Each Culvert Type and Each Output Category

Culvert Type	Average Rating	Output Category	Average Rating
RCP	4.53	Cracked	4.55
CMP	4.39	Separated	4.74
CAP	4.61	Corrosion	4.49
HDPE	4.64	Alignment	4.58
Masonry	4.63	Scour	4.48
Mixed/Other	4.42	Sedimentation	4.53
		Vegetation	4.11
		Erosion	4.88
		Blockage	4.35
		Piping	4.62

In some cases, the combination between a lack of culverts in the database and the large number of culverts that are highly rated created a situation where specific classes of culverts have empty data sets. In these cases, where no culverts have a rating of 1 or 2, it becomes impossible for an analytical model to predict an output rating of 1 or 2. In these cases, the lack of diverse data was highlighted to prevent the user misinterpreting the information produced by the model. In these cases, a hierarchy of models can still be created. The culverts for which an output rating is desired can be ranked in terms of their relative need of inspection. A complete breakdown of the SCDOT culvert database and the amount of culverts that fall into each category is shown in **Table 4.5**. Of the 60 models, each with 5 different assessment possibilities, there were 50 categories that had no culverts (16.67%).

Table 4.5: Breakdown of SCDOT Culvert Database

		AMOUNT OF CULVERTS WITH RATING:				
		1	2	3	4	5
RCP	Cracked	40	45	133	930	2758
	Separated	177	102	190	340	3124
	Corrosion	49	71	325	1035	2459
	Alignment	81	93	253	537	2954
	Scour	77	61	212	827	2721
	Sedimentation	16	14	36	106	563
	Vegetation	196	188	734	1125	1692
	Erosion	14	20	39	204	3429
	Blockage	134	217	444	940	2218
	Piping	11	12	101	669	2908
CMP	Cracked	8	5	14	31	119
	Separated	3	2	18	25	133
	Corrosion	3	10	20	46	106
	Alignment	1	9	19	26	123
	Scour	8	14	18	45	91
	Sedimentation	0	1	2	2	19
	Vegetation	2	2	22	57	99
	Erosion	1	5	5	24	134
	Blockage	8	7	17	50	107
	Piping	10	14	17	58	87
CAP	Cracked	1	0	2	3	10
	Separated	0	0	0	3	14
	Corrosion	0	0	0	3	14
	Alignment	0	0	1	1	15
	Scour	1	0	3	3	10
	Sedimentation	0	0	1	1	1
	Vegetation	1	0	3	3	10
	Erosion	0	0	0	0	16
	Blockage	0	0	0	1	16
	Piping	0	0	0	1	16
HDPE	Cracked	0	0	1	3	9
	Separated	0	0	1	0	12
	Corrosion	1	0	0	2	10
	Alignment	1	0	1	0	12
	Scour	0	0	1	1	9
	Sedimentation	0	0	0	0	0
	Vegetation	1	0	3	1	9
	Erosion	0	0	0	0	10
	Blockage	0	0	1	3	9
	Piping	0	0	1	2	8
Masonry	Cracked	9	3	9	57	552
	Separated	8	2	4	16	600
	Corrosion	7	5	32	164	419
	Alignment	2	11	40	85	491
	Scour	5	5	21	118	481
	Sedimentation	1	1	8	41	378
	Vegetation	31	31	139	128	301
	Erosion	2	1	2	10	540
	Blockage	29	35	64	170	330
	Piping	2	2	12	155	457
Mixed	Cracked	5	3	6	66	166
	Separated	6	4	5	23	208
	Corrosion	6	9	29	82	124
	Alignment	8	9	9	77	147
	Scour	5	4	11	52	173
	Sedimentation	2	1	6	25	79
	Vegetation	8	20	64	79	91
	Erosion	1	0	3	42	165
	Blockage	6	21	66	63	97
	Piping	4	1	6	16	114

Composite Ratings

While the current procedure gives an indication of the output rating for each output category it does not give an overall composite score for the health of a culvert. Using information that was received from a survey sent to state DOTs, the relative importance of each of the output categories was collected. Using these weights for the output ratings, a composite score could be assigned for each culvert.

The survey and the output variables ranked by the *SCDOT Pipe & Culvert Field Inventory and Inspection Guidelines* showed differences in the categorization of defects. The raw results of the survey are shown in **Table 4.6**. Some of the defects match well with the ten output categories classified by the inspection guide such as cracking, corrosion, and joint alignment. Other defects are not as well related to those defects described in the Inspection Guide like shape deformation. For the mapping of each of the defects addressed in the survey, the associated Inspection Guide defect is shown in **Table 4.7**.

Table 4.6: Results of Survey to State DOTs

	RCP	**CMP**
Crack	22.78%	--
Joint Misalignment	20.51%	16.14%
Joint In/Exfiltration	23.36%	18.08%
Invert Deterioration	20.00%	17.68%
Bedding Voids	13.35%	9.53%
Corrosion	--	21.22%
Shape Deformation	--	17.35%

Table 4.7: Defect Matching Between DOT Survey and Culvert Inspection Guide

DOT Survey	SCDOT Inspection Guide
Crack	Cracking
Joint Misalignment	Alignment
Joint In/Exfiltration	Separation
Invert Deterioration	Scour
Bedding Voids	Piping
Corrosion	Corrosion
Shape Deformation	Cracking

Only two sets of weights were received from the survey addressing reinforced concrete pipe culverts (RCP) and corrugated metal pipe culverts (CMP). Using these classifications, a composite score could be determined for each culvert that was ranked for the outputs that were given weights by the DOTs (**Table 4.8**)

Table 4.8: Relative Importance of Output Ratings

	RCP	CMP	Estimate (RCP)	Estimate (CMP)	All Equal
Cracked	22.78%	17.35%	22.50%	17.00%	16.67%
Separated	23.36%	18.08%	22.50%	18.00%	16.67%
Alignment	20.51%	16.14%	20.00%	16.00%	16.67%
Corrosion	0.00%	21.22%	0.00%	21.00%	16.67%
Scour	20.00%	17.68%	20.00%	18.00%	16.67%
Sedimentation	0.00%	0.00%	0.00%	0.00%	0.00%
Vegetation	0.00%	0.00%	0.00%	0.00%	0.00%
Erosion	0.00%	0.00%	0.00%	0.00%	0.00%
Blockage	0.00%	0.00%	0.00%	0.00%	0.00%
Piping	13.35%	9.53%	15.00%	10.00%	16.67%

The precision from the DOT surveys is not realistic, so less precise estimate of these weights will be used to determine the composite score for each culvert. In addition, a composite score that finds the average of all output variables was used as a control.

This composite rating provides a benefit to the user as it gives them a single value to handle, but it also gives a more continuous variation in the database of culverts. Without a composite score, there is no way to differentiate two culverts with an specific output category of 4; however, with the composite rating, other categories can separate culverts with equal ratings in some areas. It also allows the model to be corrected for a single output using an error term that made the predicted model more accurate.

CHAPTER FIVE

Logistic Regression and Artificial Neural Network Inputs

There were two types of input variables that combine to create the most accurate and effective model. The first group of variables are the variables that were documented during the culvert assessment. Of all the information documented in the culvert assessment, only some categorical information was determined to be useful based on previous deterioration models and the desired output variables. The culvert type was used to categorize each of the assessments into a different model used to predict the output criteria. The culvert dimensions, culvert shape, and number of barrels were also tracked in case they played a significant role in the predictive model.

Categorical variables including the inlet and outlet end type, end treatment, and apron type were all converted into dummy variables that could be used in the logistic regression models. These dummy variables created a binary system for each of the possible responses for each of the categorical variables. For example, the inlet end type could be flat, flared, beveled, or have no entry. Because there were four possibilities for this variable, the inlet end type was converted into four variables with a value of 0 or 1 (**Table 5.1**). It is important to note that these variables are not independent as required by the assumption built into a logistic regression.

Table 5.1: Dummy Variable Creation

INLET END TYPE				
	Flat	**Flared**	**Beveled**	**No Entry**
Flat	1	0	0	0
Flared	0	1	0	0
Beveled	0	0	1	0
No Entry	0	0	0	1

The South Carolina Department of Transportation culvert database gives an indication of the physical characteristics of a culvert, but gives no indication of the environment characteristics impacting a given culvert aside from the location of the culvert (latitude, and longitude). Consequently, an effort was made to map site specific parameters to each culvert using given latitude and longitude information. The latitude and longitude information from each culvert can be used to map data on some of the site specific parameters that can be useful in predicting the deterioration of culverts. Among the parameters that were mapped to each culvert with valid latitude and longitude inputs were temperature, precipitation, pH, and approximate surrounding runoff coefficient.

Temperature

Historical temperature information is available through the National Oceanic and Atmospheric Administration (NOAA) for weather stations across the United States. In South Carolina a total of 84 weather stations across the state had available annual average temperature information between 1981 and 2010. Some of the stations had information for many of the years between 1981 and 2010, while others had only one year of information. In each case, the average of the recorded years was used along with the latitude and longitude of each of the stations to create a contour of the average annual temperature across the state of South Carolina. This contour was created using a 2-D interpolation function using linear interpolation to estimate the temperature a given culvert and a nearest neighbor extrapolation function to prevent the temperature contour from extrapolating to unreasonable levels. In addition, the temperature data was bounded by a minimum average annual temperature of 50°F and a maximum annual average temperature of 70°F. The distribution of the stations providing average annual temperature is shown in **Figure 5.1**. The distribution of temperature follows the expected variation across the state of South Carolina with higher temperatures occurring in the lowest part of the state and the coldest annual average temperatures occurring in the upper part of the state. The blue colors indicate the lower annual average temperatures while the yellow colors represent the highest annual average temperatures.

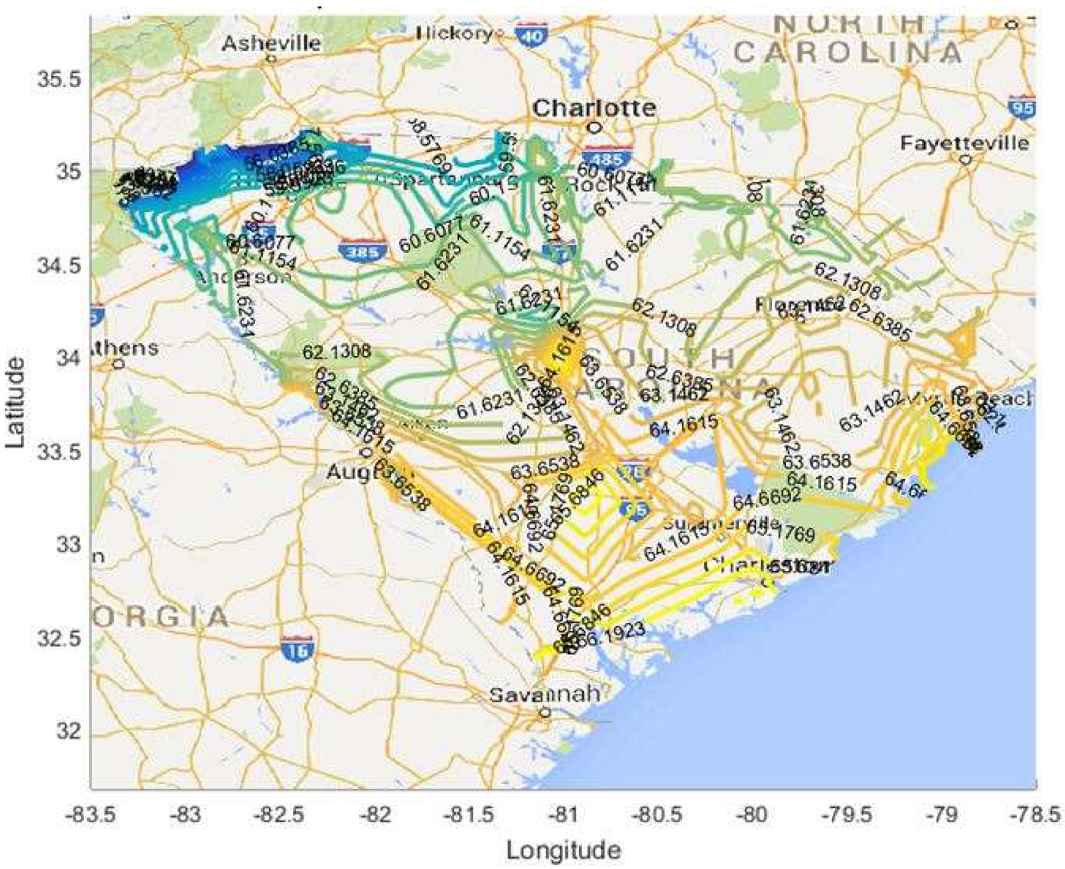


Figure 5.1: Temperature distribution across South Carolina

Precipitation

Like the annual average temperature data, annual average rainfall data was available through the NOAA in the state of South Carolina. A total of 95 weather stations across the state have annual rainfall data from 1981-2010. Again, the average annual average rainfall was used to create a contour of the rainfall across South Carolina using a 2-D interpolation function with nearest neighbor extrapolation. The data was also bounded by a minimum of 40 inches and maximum of 80 inches of annual average rainfall. The distribution of average annual rainfall across South Carolina is shown in

Figure 5.2. Like the distribution of average annual temperature, the distribution of precipitation follows the expectation that the upper portion of the state would have more precipitation than the lower part of the state. In fact, the variation of the precipitation is relatively uniform across most of the state of South Carolina until approximately Greenville, SC when the average annual precipitation increases significantly.

The average annual precipitation may give some indication as to the yearly demand on the culvert relative to other culverts, but it is limited to the fact that the floodplain controls the amount of rainfall that a culvert must funnel downstream. In addition, the average annual precipitation is not the best estimate of the expected demand, because the intensity of the rainfall and the site parameters that govern the speed at which the rainfall becomes demand on the culvert are the key factors in determining how much water a culvert must handle. Without a more detailed information, the average annual rainfall was determined to be the best proxy to estimate the demand on the culverts.

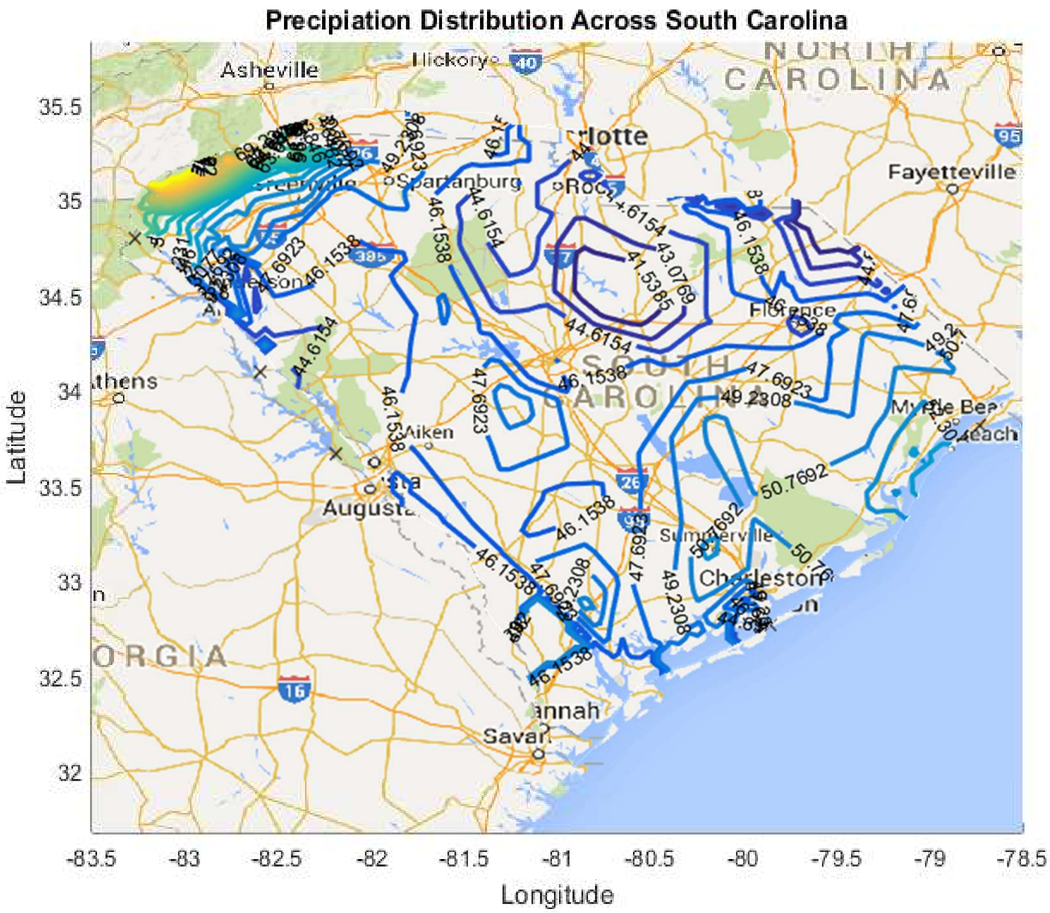


Figure 5.2: Precipitation distribution across South Carolina

pH

Similar to the temperature and precipitation information available through NOAA, statewide data on the pH of rivers and streams across South Carolina was available through the United States Geological Survey (USGS). This information corresponded to both field and lab measurements between 1997 and 2010 of 881 stations across the state in various rivers and streams at different points along these bodies of water. Using the same techniques as the temperature and precipitation data, a contour of the average measured pH was created for South Carolina using linear interpolation and nearest neighbor extrapolation. Unlike temperature and precipitation, whose effects can be assumed to linearly vary across space, pH is linked to the body of water the feeds the specific culvert. Despite the fact that pH does not exactly correlate spatially, it could serve to show the general distributions of pH across the state. In addition, larger rivers and streams may dilute the more extreme data collected from smaller bodies of water nearby. Despite this flattening effect, it is likely that the linear spatial interpolation can give some indication of the surrounding pH.

The spatial variation of pH across South Carolina can be shown in **Figure 5.3**. The predicted values of the pH of each culvert were capped at a minimum of 5 and a maximum value of 8.

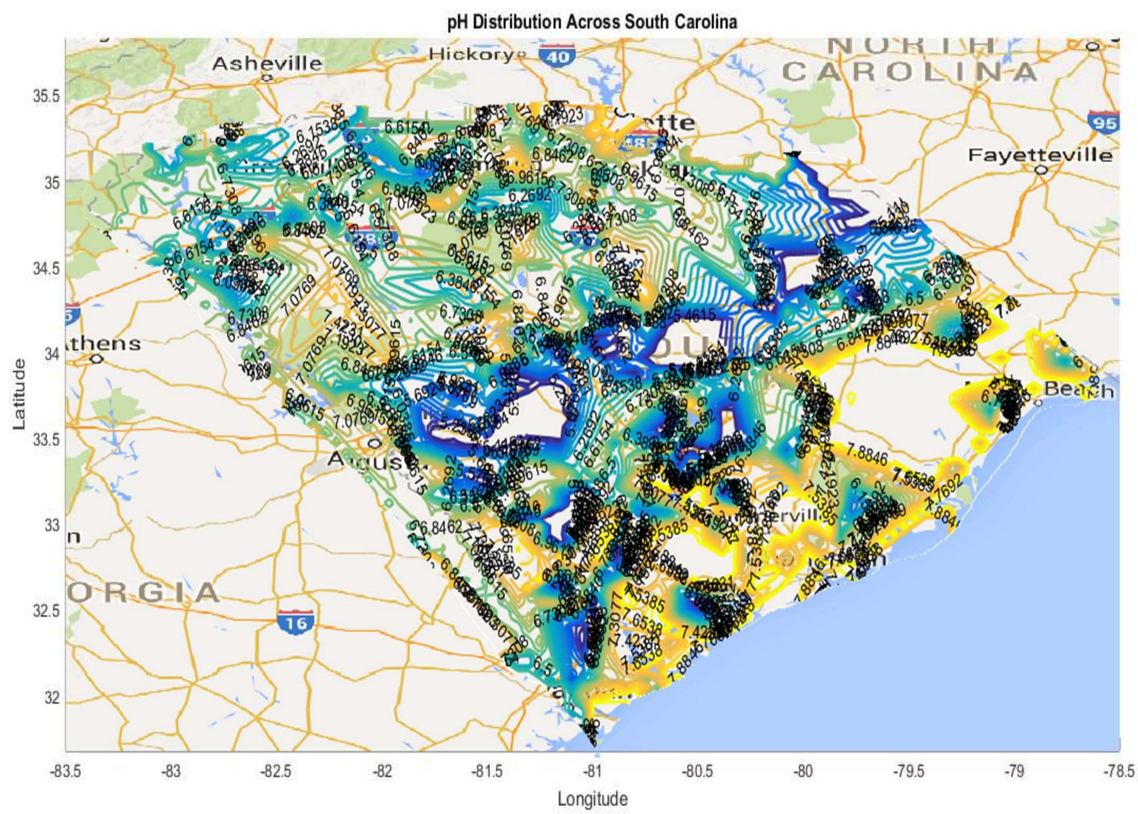


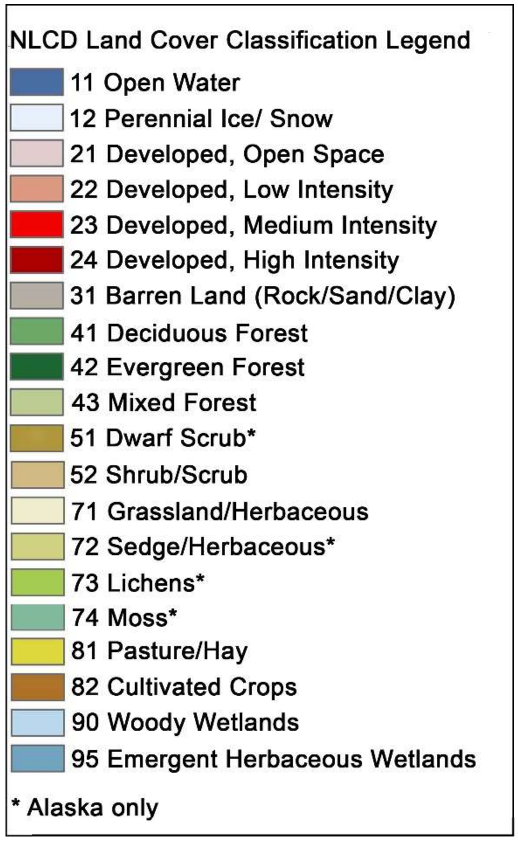
Figure 5.3: pH distribution across South Carolina

The distribution of pH values across the state of South Carolina was harder to compare to expected distributions like the distribution of temperature and precipitation. According to the values produced by the USGS there are bands of high and low pH running across the state. The first band begins at the coast and runs parallel to the coast until about halfway between Columbia, SC and Charleston, SC. This band consists of higher and more basic values of pH (>7.5). The second band contains lower more acidic values of pH (<6) and runs from the first band to approximately Columbia, SC. The rest of the state to the north and west contain relatively neutral pH values (6<pH<7.5).

Runoff Coefficient

In addition to the available online information regarding the temperature, precipitation, and pH data, the National Land Cover Database (NLCD) provides information regarding the types of land that cover the United States from 2011. Another group of site characteristics used by previous predictive models regarded the surrounding land cover. Some quantified this information as flooding potential or exposure, while others referred to it as hydraulic conditions. The NLCD provided the information in terms of a classification of each pixel for the continental United States. Each of these pixels corresponds to an approximately 10,000 square foot area. Each of these areas was assigned one of the 21 categorical land cover distinctions. These classifications were based on the Anderson Land Cover Classification System (ALCCS) (**Table 5.2** and **Figure 5.4**).

Table 5.2: ALCCS Classifications used to describe the NLCD Maps



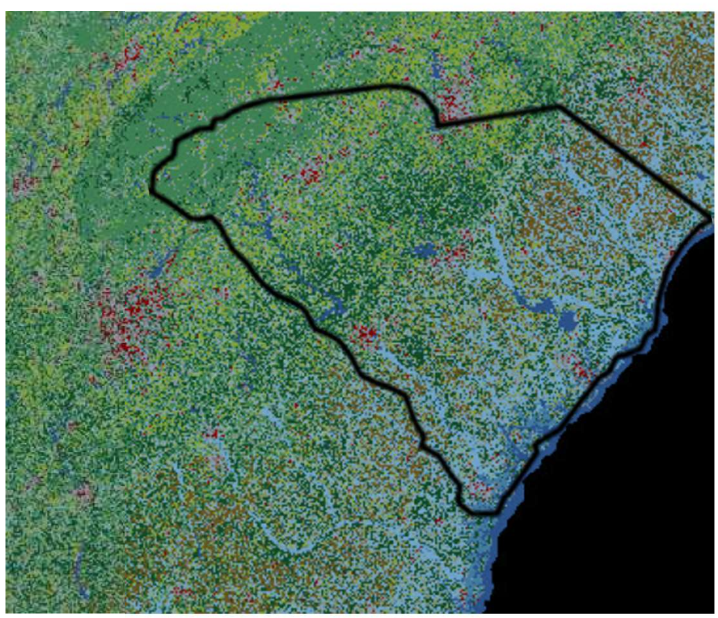


Figure 5.4: Distribution of South Carolina Land Cover (NLCD)

Because the identification number given to each pixel had no quantifiable meaning, it was converted into a scale that gave meaning to each of the land classifications. The ALCCS used to describe the pixels from the NLCD was matched to the South Carolina Requirements for Hydraulic Design guides for the runoff coefficient used in the rational method. The rational method is shown by the following equation:

$$Q = C * I * A * C_f \qquad \text{(Eq. 5.1)}$$

where: Q = discharge (cfs)

C = runoff coefficient

I = rainfall intensity (in/hr)

A = drainage area (acres)

C_f = recurrence interval coefficient

This equation is used to determine the required discharge capacity of various drainage infrastructure across South Carolina. The recurrence interval coefficient is arbitrary as it is the same for each culvert, and the mapped precipitation from the NOAA database can be an estimate to the relative rainfall intensity; however, the drainage area was difficult to estimate. With no indication of the size of the basin or body of water which feeds a specific culvert, the full equation cannot be predicted. The runoff coefficients used to estimate required discharge from the SCDOT Requirements for Hydraulic Design are shown in **Table 5.3** and the corresponding runoff coefficient assigned to the ALCCS designations shown in **Table 5.4**.

Table 5.3: South Carolina Runoff Coefficients Used in Hydraulic Design

Description (SCDOT)	Runoff Coefficient	Description (SCDOT)	Runoff Coefficient
Pavements & Roofs	0.90	Side Slopes, Earth	0.60
Earth shoulders	0.50	Side Slopes, Turf	0.30
Drives & Walks	0.75	Median Areas, Turf	0.25
Gravel Pavements	0.50	Cultivated Land, Clay & Loam	0.50
City Business Areas	0.80	Cultivated Land, Sand & Gravel	0.25
Unpaved Road, Sandy Soils	0.34	Industrial Areas, Light	0.50
Unpaved Road, Silty Soils	0.35	Industrial Areas, Heavy	0.60
Unpaved Road, Clay Soils	0.40	Parks & Cemeteries	0.10
Aparment Dwelling Areas	0.50	Playgrounds	0.20
Suburban, Normal Residential	0.45	Woodland & Forest	0.10
Dense Residential Sections	0.60	Meadows & Pasture Land	0.25
Lawns, Sandy Soils	0.10	Unimproved Areas	0.10
Lawns, Heavy Soils	0.17	Rail Yards	0.25
Grass Shoulders	0.25	Expressways & Freeways	0.00

Table 5.4: ALCCS Pixel Data and Corresponding Runoff Coefficient from SCDOT

Pixel ID	Description (NLCD)	Runoff Coefficient	SCDOT Description
11	Open Water	0.00	--
12	Perennial Ice/Snow	0.00	--
21	Developed, Open	0.45	Suburban, Normal Residential
22	Developed, Low	0.50	Aparment Dwelling Areas
23	Developed, Medium	0.55	Aparment Dwelling Areas/ Dense Residential Sections
24	Developed, High	0.60	Dense Residential Sections
31	Barren Land (Rock/Sand/Clay)	0.40	Unpaved Road, Clay Soils
41	Deciduous Forest	0.10	Woodland & Forest
42	Evergreen Forest	0.10	Woodland & Forest
43	Mixed Forest	0.10	Woodland & Forest
51	Dwarf Scrub	0.10	Woodland & Forest
52	Shrub/Scrub	0.10	Woodland & Forest
71	Grassland/Herbaceous	0.25	Meadows & Pasture Land
72	Sedge/Herbaceous	0.25	Meadows & Pasture Land
73	Lichens	0.25	Meadows & Pasture Land
74	Moss	0.25	Meadows & Pasture Land
81	Pasture/Hay	0.30	Side Slopes, Turf
82	Cultivated Crops	0.40	Unpaved Road, Clay Soils
90	Woody Wetlands	0.00	--
95	Emergent Herbaceous Wetlands	0.00	--
0	No Description	0.00	--

Once the parameters were mapped and converted into a quantifiable and meaningful value, the pixel data could be consolidated into larger areas that could be applied to a culvert. With each pixel only covering an average of 9,000 square feet (0.000325 square miles), mapping the runoff coefficient of a single pixel to each culvert would likely result in some significant error and would not capture the effect of the surrounding area as each culvert's runoff coefficient would be the average of the drainage area supplying the associated stream or river. Consequently, a square area of 25 pixels by 25 pixels was averaged to give a more representative sample of the average runoff coefficient. The new area covered by each data point corresponds to approximately 5,575,000 square feet, 0.20 square miles, or 128 acres. These data points were then used to assign a culvert an average runoff coefficient for the surrounding 0.20 square miles using the nearest pixel associated with the culvert's latitude and longitude.

Input Variable Combinations

In producing the most effective model, it is important to determine which combinations of input variables are most effective at predicting various output variables. Certain outputs may be better predicted using a more diverse or complex combination of input variables. In order to organize the testing of these models and to limit the number of trials for each model, a table of the available input variable was created (**Table 5.5**). These inputs were then combined to form trial models that would be evaluated to determine which models produced the best results as far as predicting the ten associated output variables (**Table 5.6**). The first ten combinations of inputs contain only variables that are linearly added to give the final prediction. The last three combinations of variables have a special that is a multiplicative combination of two or more variables. In an attempt to capture a variable estimating the demand on a culvert, the precipitation and the runoff coefficient estimate were multiplied together. Furthermore, this value was divided by characteristics of height and width to estimate the area of a culvert to give an estimation of the ratio between demand and capacity. A neural network's hidden neuron layer can be used to determine some of the more complex relationships between input variables; however, a logistic regression model requires the manipulation of such inputs by the user. After the 13 original combinations had been evaluated, the most accurate predictive model was used for each culvert type and output.

Table 5.5: Possible Input Variables and Assumed Importance

INPUT VARIABLES		
Variable Name	**ID #**	**Assigned Importance**
Age	1	1
pH	2	1
Runoff Coefficient	3	1
Temperature	4	1
Precipitation	5	1
Num Barrels	6	2
Culvert Shape	7	2
Width	8	2
Height	9	2
Length	10	2
Inlet End Type	11	3
Inlet End Treatment	12	3
Inlet Apron Type	13	3
Outlet End Type	14	3
Outlet End Treatment	15	3
Outlet Apron Type	16	3

Table 5.6: Combinations of Input Variables Tested

COMBINATIONS		
Combination ID	**Input Variables**	**Combined Inputs**
1	1,2,3,4,5	--
2	1,2,3,4	--
3	1,2,3,5	--
4	1,2,4,5	--
5	1,3,4,5	--
6	1-5,8,9,10	--
7	1-5,6	--
8	1-5,7	--
9	1-5,11-16	--
10	1,2,4	3 x 5
11	1,2,4	3 x 5 / 8
12	1,2,4	(3 x 5)/(8 x 9)
13	1-5,6-10	--

CHAPTER SIX

Model Creation and Discussion

Logistic Regression Model Creation

In order to create the logistic regression models for each of the 13 combinations, the MATLAB built-in function 'mnrfit' was used. The function creates the coefficients of a multinomial logistic regression for a set of given inputs and corresponding outputs using the maximum log-likelihood function. These coefficients follow the form of Eq. 3.3. The coefficients that were returned from the fitting function were used in the built-in MATLAB function, 'mnrval' which created a probabilistic estimate based on the inputs of an associated culvert and the coefficients of the model that had been created. The result of this function is a probability distribution for each culvert giving an indication of the likelihood that a culvert is rated 1-5. Assuming a linear relationship between the culvert ratings means that a non-integer estimate was produced using the probability distribution and the value of the associated output, 1-5. This predicted value can be compared to the measured output value and the statistical indicators of the effectiveness of the model can be calculated. In the case of each of the 13 combinations, the area under the ROC curve that was produced for each model was used as the primary indicator of the accuracy of the model. The selection of this criteria was based largely on the versatility of the ROC curve in determining a model's ability to separate the data in categories outlined by the SCDOT.

The 13 combinations of input variables were used to create 13 models, each addressing 6 culvert types and 10 output variables for a total of 780 models. For each of the models four ROC curves were created to address the model's ability to separate an output rating of 1 from 2-5, 1-2 from 3-5, 1-3 from 4-5, and 1-4 from 5. The area underneath these curves can range from 0.5 to 1.0, with a higher score indicating a more accurate model. An ROC curve can produce an area under the curve of 0.0 usually indicating that the model cannot predict that specific value, because there is not a culvert with that specific rating. For some of the culverts with fewer responses, this became an issue in determining the effectiveness of a model. Because this problem is independent of the combination of input variables used to create this model, the ROC curves could still be used as a measure of accuracy. In other cases, where the number of observed culverts remained low, a large number of input variables can make it impossible to produce a model whose log-likelihood function converges. Similarly, when too few or insignificant input variables were used, the log-likelihood function would not converge. In these cases, an area under the ROC curve of 0.0 could be possible and understood to indicate a category where fewer responses were available.

The results of the 13 models addressing the 6 culvert types and 10 output variables is shown were **Table 6.1.** The values corresponding to the maximum area under the 4 ROC curves for each model is highlighted indicating the best combination of input variables.

Table 6.1: Area Under Curve Results (Logistic Regression)

		COMBINATION NUMBER													
		1	10	11	12	13	2	3	4	5	6	7	8	9	Max Area
RCP	**Cracked**	2.592	2.439	2.421	2.363	2.672	2.428	2.313	2.560	2.550	2.656	2.601	2.633	2.723	9
	Separated	2.457	2.382	2.356	2.583	2.924	2.377	2.244	2.457	2.464	2.827	2.466	2.728	2.732	13
	Corrosion	2.702	2.541	2.526	2.444	2.781	2.546	2.500	2.672	2.687	2.791	2.701	2.737	2.845	9
	Alignment	2.762	2.604	2.585	2.544	2.822	2.593	2.409	2.753	2.752	2.781	2.773	2.845	2.938	9
	Scour	2.941	2.671	2.655	2.686	2.904	2.652	2.638	2.945	2.940	2.924	2.946	2.945	2.993	9
	Sedimentation	2.807	2.754	2.732	2.758	2.945	2.751	2.416	2.791	2.810	2.921	2.834	0.000	2.956	9
	Vegetation	2.391	2.229	2.314	2.271	2.458	2.244	2.296	2.373	2.358	2.494	2.400	2.400	2.572	9
	Erosion	2.838	2.735	2.720	2.856	3.101	2.724	2.287	2.838	2.827	3.038	2.856	2.907	3.081	13
	Blockage	2.367	2.268	2.271	2.229	2.455	2.260	2.240	2.352	2.324	2.459	2.366	2.371	2.611	9
	Piping	2.478	2.378	2.408	2.375	2.729	2.378	2.312	2.431	2.474	2.682	2.539	2.530	2.826	9
CMP	**Cracked**	2.615	2.431	2.412	2.523	2.977	2.472	2.399	2.600	2.582	2.940	2.683	2.674	0.000	13
	Separated	2.873	2.716	2.755	2.850	2.955	2.784	2.646	2.745	2.732	3.202	2.935	2.840	0.000	6
	Corrosion	2.798	2.560	2.488	2.808	3.147	2.577	2.765	2.751	2.606	3.157	2.806	2.866	0.000	6
	Alignment	3.295	2.899	2.859	3.080	3.226	2.931	3.054	3.265	3.258	3.171	3.299	3.328	0.000	8
	Scour	3.136	2.449	2.491	2.706	2.807	2.476	2.829	3.106	3.161	2.911	3.162	3.118	0.000	7
	Sedimentation	2.731	2.594	2.689	2.708	2.174	2.552	2.631	2.444	2.684	2.687	2.731	0.000	0.000	1
	Vegetation	3.283	2.966	2.915	3.013	3.029	2.959	3.244	3.293	3.298	3.114	3.311	3.183	0.000	7
	Erosion	3.320	2.950	2.980	2.266	2.633	3.033	3.180	3.316	3.183	2.583	3.324	3.296	0.000	7
	Blockage	2.818	2.455	2.460	2.443	2.667	2.456	2.506	2.777	2.594	2.745	2.803	2.661	0.000	1
	Piping	2.776	2.247	2.371	2.627	2.950	2.241	2.581	2.775	2.788	2.898	2.801	2.839	0.000	13
CAP	**Cracked**	2.954	2.954	2.371	1.125	1.667	3.004	2.614	2.521	3.190	2.000	2.987	0.000	0.000	5
	Separated	1.000	0.810	0.857	1.000	1.000	0.810	0.905	1.000	1.000	1.000	1.000	0.000	0.000	1
	Corrosion	1.000	0.929	1.000	1.000	1.000	0.929	0.667	0.976	1.000	1.000	1.000	0.000	0.000	1
	Alignment	1.633	1.467	1.667	1.000	1.000	1.467	1.500	1.900	1.500	1.000	1.700	0.000	0.000	4
	Scour	3.598	3.326	2.974	1.750	1.667	3.306	3.411	3.233	3.507	1.833	3.598	0.000	0.000	1
	Sedimentation	1.500	2.000	2.000	0.000	0.000	2.000	2.000	2.000	1.500	0.000	2.000	0.000	0.000	10
	Vegetation	3.072	2.856	3.296	1.000	1.667	2.837	2.986	2.861	2.942	1.750	2.534	0.000	0.000	11
	Erosion	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	--
	Blockage	1.000	0.938	0.875	1.000	1.000	0.938	1.000	1.000	1.000	1.000	1.000	0.000	0.000	1
	Piping	1.000	1.000	1.000	0.000	0.000	1.000	1.000	1.000	1.000	0.000	1.000	0.000	0.000	1
HDPE	**Cracked**	2.000	1.722	1.625	1.800	2.000	1.639	1.611	1.861	1.528	0.000	1.972	0.000	0.000	1
	Separated	1.417	1.000	1.000	1.000	1.000	1.167	1.000	1.000	1.417	0.000	1.583	0.000	0.000	7
	Corrosion	2.133	3.717	3.360	2.433	2.111	3.450	2.317	1.867	2.617	0.000	1.767	0.000	0.000	10
	Alignment	1.875	3.263	3.068	1.891	1.656	3.436	2.824	1.667	2.788	0.000	2.196	0.000	0.000	2
	Scour	1.889	1.833	1.750	1.643	1.500	1.389	1.944	1.467	1.622	1.643	1.889	0.000	0.000	3
	Sedimentation	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	--
	Vegetation	2.761	3.194	3.289	2.677	2.700	3.271	3.114	2.936	3.154	0.000	3.171	0.000	0.000	11
	Erosion	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	--
	Blockage	1.889	1.889	1.781	1.679	1.000	1.833	1.889	1.528	1.722	0.000	1.889	0.000	0.000	1
	Piping	1.958	1.958	1.857	1.444	1.000	1.917	1.958	1.483	1.875	1.889	1.958	0.000	0.000	1
Masonry	**Cracked**	2.586	2.336	2.275	2.280	2.943	2.341	2.552	2.454	2.571	2.880	2.617	2.636	0.000	13
	Separated	2.530	2.536	2.504	2.391	2.881	2.525	2.436	2.486	2.512	2.850	2.567	2.575	0.000	13
	Corrosion	2.754	2.562	2.405	2.499	3.085	2.602	2.721	2.664	2.711	3.066	2.751	2.790	0.000	13
	Alignment	3.510	3.337	3.339	3.303	3.585	3.330	3.445	3.504	3.492	3.601	3.539	3.513	0.000	6
	Scour	2.984	2.799	2.796	2.691	3.022	2.797	2.949	2.898	3.032	3.038	3.063	3.010	0.000	7
	Sedimentation	3.370	3.156	3.168	3.160	3.123	3.174	2.921	3.378	3.298	3.474	3.401	3.372	0.000	6
	Vegetation	2.804	2.753	2.782	2.673	2.754	2.754	2.702	2.783	2.806	2.842	2.768	2.820	0.000	6
	Erosion	2.818	2.852	2.864	2.817	3.170	2.819	2.912	2.806	2.705	3.220	2.853	2.838	0.000	6
	Blockage	2.298	2.384	2.371	2.218	2.575	2.385	2.286	2.214	2.334	2.514	2.417	2.321	0.000	13
	Piping	3.347	3.257	3.318	3.179	3.435	3.270	3.148	3.445	3.224	3.477	3.344	3.357	0.000	6
Mixed	**Cracked**	2.947	2.897	2.675	2.859	3.323	2.890	2.878	2.540	2.786	3.270	2.904	0.000	0.000	13
	Separated	2.458	2.480	2.508	2.635	2.961	2.474	2.474	2.196	2.407	2.815	2.438	0.000	0.000	13
	Corrosion	2.811	2.662	2.565	2.693	3.015	2.674	2.750	2.641	2.557	2.950	2.931	0.000	0.000	13
	Alignment	2.608	2.646	2.708	2.272	2.714	2.651	2.619	2.550	2.226	2.824	2.646	0.000	0.000	6
	Scour	2.647	2.442	2.416	2.636	2.892	2.420	2.561	2.712	2.611	2.874	2.663	0.000	0.000	13
	Sedimentation	3.030	3.124	3.063	3.107	3.105	3.124	2.635	3.016	2.643	3.153	3.058	0.000	0.000	6
	Vegetation	2.512	2.534	2.502	2.431	2.785	2.527	2.448	2.433	2.315	2.681	2.582	0.000	0.000	13
	Erosion	2.149	2.593	2.366	1.322	1.617	2.319	2.103	3.256	2.038	1.448	2.358	0.000	0.000	4
	Blockage	2.756	2.740	2.741	2.692	2.740	2.772	2.735	2.636	2.505	2.988	2.743	0.000	0.000	6
	Piping	2.602	2.801	2.600	2.366	2.474	2.773	2.785	2.453	2.391	3.319	2.586	0.000	0.000	6
	Total Models	10	2	2	0	13	1	1	2	1	11	5	1	8	57

Artificial Neural Network Model Creation

Like the logistic regression, the 13 combinations of input variables were used to create a total of 780 total neural network models. The three general functions governing the behavior of the neural network model are the weighting function, the bias function, and the transfer function. The transfer function is effected by the number of neurons used to model the relationships between both the input variables and each other and the input variables and the output variables. Because these relationships can often be complex, the number of neurons used in the transfer was varied from 1 neuron to 10 neurons. The creation of the neural network is based on the MATLAB built-in Neural Network toolbox. The toolbox allows the user to specify the performance function (mean-squared error and mean-absolute error); however, in an attempt to stay consistent with the measure of the success of the predictive models between logistic regression and neural network models, the ROC curves were created with each of the models. The associated total area under the four ROC curves was used as the measure of the performance of the models. In each case, the maximum area under the curve was used to determine how many neurons created the best model. Similarly, the best of the 13 combinations of input variables was used to determine the optimal input variable combination (**Table 6.2**).

Table 6.2: Area Under Curve Results (Artificial Neural Network)

		COMBINATION NUMBER													
		1	10	11	12	13	2	3	4	5	6	7	8	9	Max Area
RCP	**Cracked**	2.865	2.747	2.696	2.647	2.806	2.750	2.608	2.834	2.881	2.836	2.897	2.883	2.772	7
	Separated	2.583	2.441	2.485	2.591	2.954	2.462	2.472	2.540	2.499	2.904	2.570	2.874	2.874	13
	Corrosion	2.948	2.807	2.768	2.755	2.882	2.813	2.749	2.862	2.877	2.940	2.905	2.940	2.850	1
	Alignment	3.102	2.970	2.968	2.801	2.992	3.006	2.797	3.186	3.041	3.030	3.113	3.123	3.096	4
	Scour	3.086	2.917	2.954	2.890	3.078	2.906	2.854	3.054	3.057	3.017	3.102	3.087	3.118	9
	Sedimentation	2.817	2.820	2.735	2.764	2.862	2.885	2.633	2.824	2.801	3.012	2.810	2.871	3.112	9
	Vegetation	2.780	2.646	2.665	2.607	2.695	2.705	2.549	2.761	2.716	2.717	2.731	2.747	2.706	1
	Erosion	3.075	2.834	2.862	3.009	2.972	2.893	2.775	2.967	2.984	3.067	3.097	3.025	2.941	7
	Blockage	2.685	2.580	2.571	2.447	2.650	2.560	2.495	2.615	2.573	2.590	2.610	2.597	2.724	9
	Piping	2.859	2.821	2.710	2.685	2.831	2.842	2.711	3.004	2.766	2.759	3.056	2.912	2.995	7
CMP	**Cracked**	3.117	3.077	3.095	3.119	3.130	3.048	2.884	3.156	3.070	3.286	3.068	3.061	3.118	6
	Separated	3.126	3.125	3.174	3.368	3.307	3.284	3.238	3.059	3.205	3.651	2.965	3.290	3.307	6
	Corrosion	3.307	3.138	3.268	3.040	3.213	3.181	2.948	3.421	3.105	3.234	3.219	3.299	3.168	4
	Alignment	3.259	3.139	3.118	3.186	3.127	3.279	3.206	3.332	3.304	3.266	3.309	3.420	3.462	9
	Scour	3.272	3.225	2.783	2.750	2.890	3.004	3.146	3.121	3.110	3.130	3.189	3.234	3.214	1
	Sedimentation	2.863	2.789	2.894	2.830	2.496	2.678	2.772	2.552	2.800	2.544	2.762	2.592	2.822	11
	Vegetation	3.280	3.344	3.185	2.911	3.458	3.000	3.176	3.330	3.103	3.218	3.304	3.422	3.199	13
	Erosion	3.441	3.454	3.377	2.376	2.477	3.267	3.423	3.450	3.245	2.472	3.503	3.307	3.364	7
	Blockage	2.980	2.762	2.749	2.620	3.071	2.724	2.678	3.014	2.723	2.988	3.000	2.837	3.084	9
	Piping	3.179	3.012	3.141	3.208	3.161	3.108	3.037	2.953	3.061	3.140	3.030	3.142	3.083	12
CAP	**Cracked**	2.981	3.059	3.104	2.153	2.250	3.110	3.031	3.187	2.851	2.500	3.071	2.995	3.068	4
	Separated	1.000	0.976	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
	Corrosion	1.000	0.976	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.976	1.000	1.000	1
	Alignment	2.000	1.933	2.000	1.000	1.000	1.967	2.000	1.933	1.933	1.000	1.933	2.000	1.833	1
	Scour	3.233	2.924	3.098	2.417	2.417	3.117	2.992	3.098	3.209	2.333	3.077	3.136	3.016	1
	Sedimentation	2.000	2.000	2.000	0.000	0.000	2.000	2.000	2.000	2.000	0.000	2.000	2.000	2.000	1
	Vegetation	2.802	2.988	2.892	2.000	2.417	2.912	2.679	3.123	3.089	2.500	2.995	2.980	3.183	9
	Erosion	--	--	--	--	--	--	--	--	--	--	--	--	--	--
	Blockage	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
	Piping	1.000	1.000	1.000	0.000	0.000	1.000	1.000	1.000	1.000	0.000	1.000	1.000	1.000	1
HDPE	**Cracked**	1.889	1.889	1.784	1.900	2.000	1.806	1.806	1.861	1.778	2.000	1.972	1.889	1.806	13
	Separated	1.500	1.500	1.500	1.500	1.500	1.500	1.500	1.500	1.500	1.500	1.500	1.500	1.500	1
	Corrosion	2.867	2.883	2.707	2.833	2.952	2.867	2.933	2.967	2.717	2.952	2.717	2.867	2.900	4
	Alignment	2.923	2.917	3.000	3.000	3.000	2.958	2.833	2.583	2.798	2.833	2.833	2.923	2.881	11
	Scour	2.000	2.000	1.715	1.571	1.589	2.000	2.000	1.422	1.611	2.000	1.722	2.000	1.889	1
	Sedimentation	0.956	1.122	1.153	1.571	1.536	2.000	1.778	1.367	1.611	1.643	1.178	0.956	1.300	2
	Vegetation	2.699	3.067	2.919	2.894	3.000	2.917	2.765	3.169	2.969	2.967	2.889	2.699	3.030	4
	Erosion	--	--	--	--	--	--	--	--	--	--	--	--	--	--
	Blockage	1.722	1.944	1.628	1.750	1.889	1.917	1.861	1.417	1.833	2.000	1.611	1.722	1.889	6
	Piping	1.958	2.000	1.651	1.417	1.944	2.000	1.958	1.733	1.817	2.000	1.958	1.958	1.833	10
Masonry	**Cracked**	2.901	3.028	2.791	2.744	3.045	2.887	2.947	2.830	3.020	3.080	3.191	2.890	3.106	7
	Separated	2.841	2.774	2.829	2.759	3.014	2.800	2.720	2.869	2.652	2.916	2.705	2.787	3.036	9
	Corrosion	3.418	3.162	3.081	3.125	3.127	3.044	3.387	3.230	3.022	3.213	3.546	2.837	3.308	7
	Alignment	3.716	3.680	3.664	3.674	3.730	3.660	3.521	3.645	3.700	3.733	3.683	3.647	3.651	6
	Scour	3.255	3.174	3.138	3.156	3.504	3.175	3.202	3.367	3.382	3.402	3.233	3.399	3.464	13
	Sedimentation	3.411	3.293	3.458	3.387	3.189	3.402	3.121	3.521	3.321	3.672	3.541	3.446	3.786	9
	Vegetation	3.137	3.149	3.170	3.224	3.040	3.067	3.017	3.126	3.224	3.122	3.169	3.232	3.199	8
	Erosion	3.195	3.069	2.791	3.105	3.285	2.776	3.279	3.000	3.343	3.514	3.214	3.514	3.121	8
	Blockage	3.093	2.986	3.013	2.920	3.025	2.987	2.867	2.935	3.038	3.030	2.987	2.965	2.949	1
	Piping	3.547	3.540	3.534	3.614	3.376	3.499	3.384	3.695	3.552	3.548	3.588	3.477	3.714	9
Mixed	**Cracked**	2.953	2.689	2.630	3.021	2.828	2.981	2.851	2.634	3.234	3.344	2.848	3.174	3.521	9
	Separated	2.900	2.686	2.630	2.472	2.637	2.729	2.714	2.671	2.698	2.915	2.781	2.897	3.265	9
	Corrosion	3.024	3.071	3.051	3.226	2.950	3.063	2.774	3.085	3.064	3.060	3.053	3.071	3.431	9
	Alignment	3.097	3.001	2.960	3.072	3.170	2.931	2.722	3.069	3.118	3.114	2.972	3.055	3.110	13
	Scour	2.602	2.690	2.658	2.965	2.724	2.629	2.717	2.842	2.981	3.104	2.752	2.860	3.265	9
	Sedimentation	3.361	3.185	3.194	3.308	3.137	3.138	3.006	3.302	2.897	3.225	3.086	2.939	3.308	1
	Vegetation	2.728	2.645	2.818	2.777	2.956	2.704	2.633	2.748	2.638	2.723	2.609	2.640	3.028	9
	Erosion	3.044	2.998	2.942	2.023	2.132	2.876	2.993	3.043	3.039	2.311	3.057	3.276	3.235	8
	Blockage	2.989	2.886	2.906	2.891	3.018	2.978	2.739	2.997	3.013	3.090	2.964	3.065	2.948	6
	Piping	3.046	2.929	3.023	2.622	3.545	2.858	3.158	2.866	2.668	3.530	2.783	3.423	3.174	13
	Total Models	14	2	2	1	6	0	0	5	0	5	6	3	14	58

Example of ROC Curve Analysis

In order to compare a model's ability to separate date visually, the ROC plots were created for each of the models whose AUC proved to be the largest (Appendix A). The plots of the ROC curves provided information regarding a model's ability to separate the data into each of the five categories (1, 2, 3, 4, and 5). For example purposes models which showed a strong ability to differentiate these categories, and a model which showed strong and weak abilities to separate such information are shown in **Figure 6.1** and **Figure 6.2** respectively.

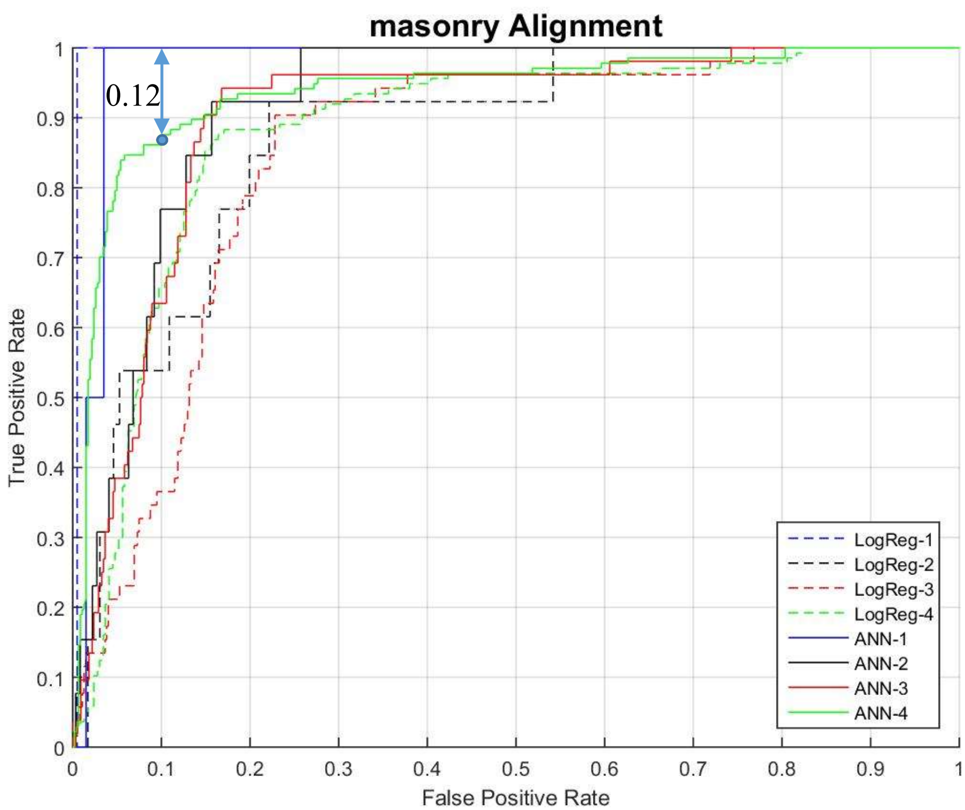


Figure 6.1: ROC Curve Describing Masonry Alignment Model

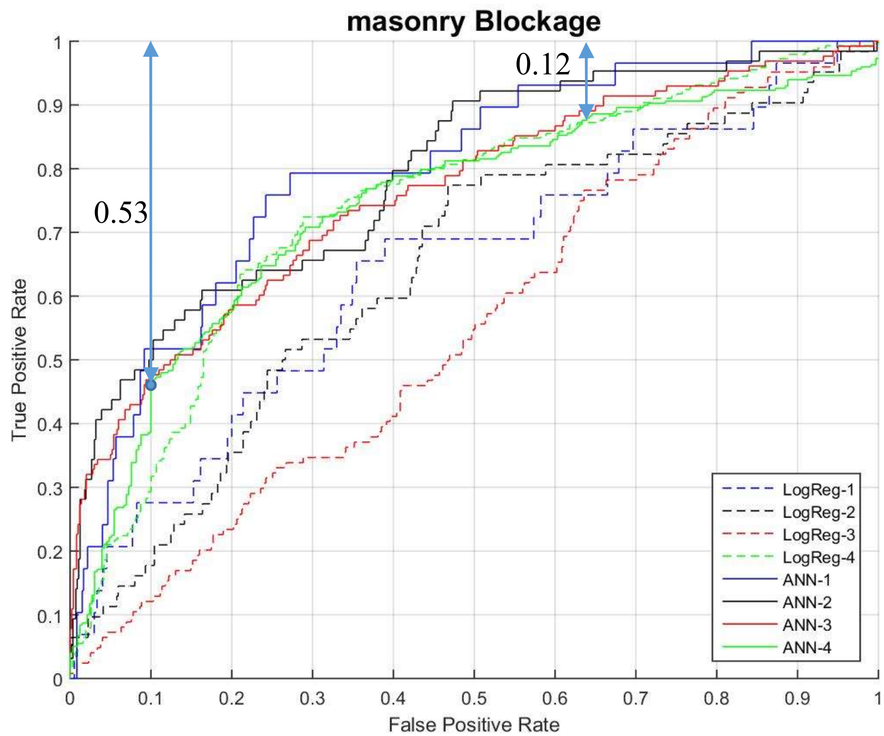


Figure 6.2: ROC Curve Describing Masonry Blockage Model

In examining **Figure 6.1** describing the Masonry Alignment model it is seen that the total area under the four curves is relatively high (3.733 for Artificial Neural Network and 3.601 for Logistic Regression). The number of true positives that are predicted by the model are accompanied by very few false positives. For the line labeled ANN-4, a true positive is a culvert that is labeled with a predicted alignment rating of 4 or less whose actual rating is four or less. A false positive is a culvert labeled with a predicted alignment rating of greater than four whose actual rating is less than four. For the other models, 3, 2, and 1 we can also examine their ability to maximize the culverts correctly identified as in poor condition; however, it may be of more interest to determine how many culverts with a poor rating are missed by the model. To perform this calculation, you must take the difference between 1 and the true positives. This value is the number of true positives that have been missed by the model. It can be seen that in the case of the indicated point along the line of the ANN-4 ROC curve that 10% of the data predicted by the model will be falsely identified as less than or equal to four. Furthermore, 88% of the data with an actual score of less than or equal to four will be predicted as such, with 12% of these data points missing.

In examining **Figure 6.2**¸we see a model that does a poor job of identifying the separation of data as compared to the model shown in **Figure 6.1**. The corresponding area under the four curves total to 3.093 for the Artificial Neural Network model and 2.575 for the Logistic Regression Model for the model predicting masonry blockage. When examining the same point on the ANN-4 ROC curve, the model predicts 10% of the data as a false positive, but it only correctly identifies 47% of the data as having a score of less than or equal to four. This corresponds to a total of 53% of the data that is misidentified as having a score higher than their true score. As the number of false positives increases, the amount of correctly identified culverts also increase but significantly slower than the model predicting masonry alignment. In order to achieve the same amount of correctly identified culverts as **Figure 6.1** (88%) nearly 65% of the culverts with an true rating higher than 4 would receive a false positive rating.

A final observation that can be made by the models is the comparison between the Artificial Neural Network model and Logistic Regression model. In terms of the performance of a model in regards to the area under the curve, it is visually easy to determine which model performs better and in which situations. For the examples shown in **Figure 6.1**, the ANN model performs better in most cases. For the presented ROC curves, the only case where the Logistic Regression model shows an advantage is in the differentiation of the culverts rated 1.

Additional Model Modifications

Using the best model input combinations for both the logistic regression and the artificial neural network two final models addressing the six different culvert types and ten different output variables. These two models can, at this stage, give a prediction of the desired output on a continuous sale from 1.0-5.0. In order to further develop the model as an efficient tool to determining the culverts in need of physical assessment, it is important to determine the optimal threshold of allowable falsely identified good condition and poor condition culverts. For example, the cost of examining a large percentage of culverts that may be in good condition needs to be limited; however, the fewer culverts that are marked as poorly rated culverts, the more culverts in need of inspection may be missed. When using ROC curves as an indication of a model's accuracy, it is important to note that the ROC curve denotes the ability for the model to separate the data into groups while showing the tradeoff between true positive results and false positive results. Using an ROC curve allows the user to select a threshold value after the model is created that indicates the approximate amount of false positive results to be expected by the model.

Selecting the appropriate threshold can be done through two primary methods. The first weights the cost of a false positive and false negatives in a cost matrix. The cost matrix that is used to determine the optimal threshold point on the ROC curve is shown by **Table 6.3.**

Table 6.3: Cost Emphasis Matrix

Actual\Model	Positive	Negative
Positive	P|P	N|P
Negative	P|N	N|N

In this matrix, the positive classification represents culverts that are less than or equal to a given output (1-4). Conversely, the negative category represents culverts that are greater than a given output rating. For example, at an output rating of 3, positive culverts are denoted as culverts less than or equal to 3, while negative culverts are shown as those culverts greater than 3. The ratio of these scores gave an indication of the consequence of falsely identifying culverts with better ratings as having a poor rating, as well as denoting culverts that are in need of inspection and repair as in good condition. In the case of the South Carolina Department of Transportation, the consequence of failing it identify a culvert in need of repair (N|P) would be much greater than the consequence of identifying a culvert that is in good condition as one in need of repair (P|N). Typically, there is no cost associated with correctly identifying good condition or poor condition culverts; however, the model can account for situations that would require these values to be non-zero.

For the case of culvert prediction, a sample cost matrix is given as the following:

Actual/Model	Positive	Negative
Positive	0	10
Negative	1	0

This matrix indicates that the cost of missing a culvert in poor condition is 10 times worse than accidentally identifying a culvert as in worse condition than it is in reality. Using this arbitrary threshold limit, the optimal point on the ROC curve could be discovered and the threshold for these culverts could be set to optimize the 'cost' of falsely identifying the culvert's rating. In an example showing the threshold values calculated for the model describing RCP culverts and their separation output, the optimal values of each the four thresholds is shown in **Table 6.4**. These points are plotted on the associated ROC curves in **Figure 6.3**.

Table 6.4: Optimal Points for RCP Separation Model

Logistic Regression			Artificial Neural Network		
Threshold	**False Postive**	**True Positive**	**Threshold**	**False Postive**	**True Positive**
1	0.165	0.588	1	0.141	0.495
2	0.338	0.697	2	0.250	0.607
3	0.573	0.863	3	0.263	0.613
4	0.687	0.942	4	0.675	0.933

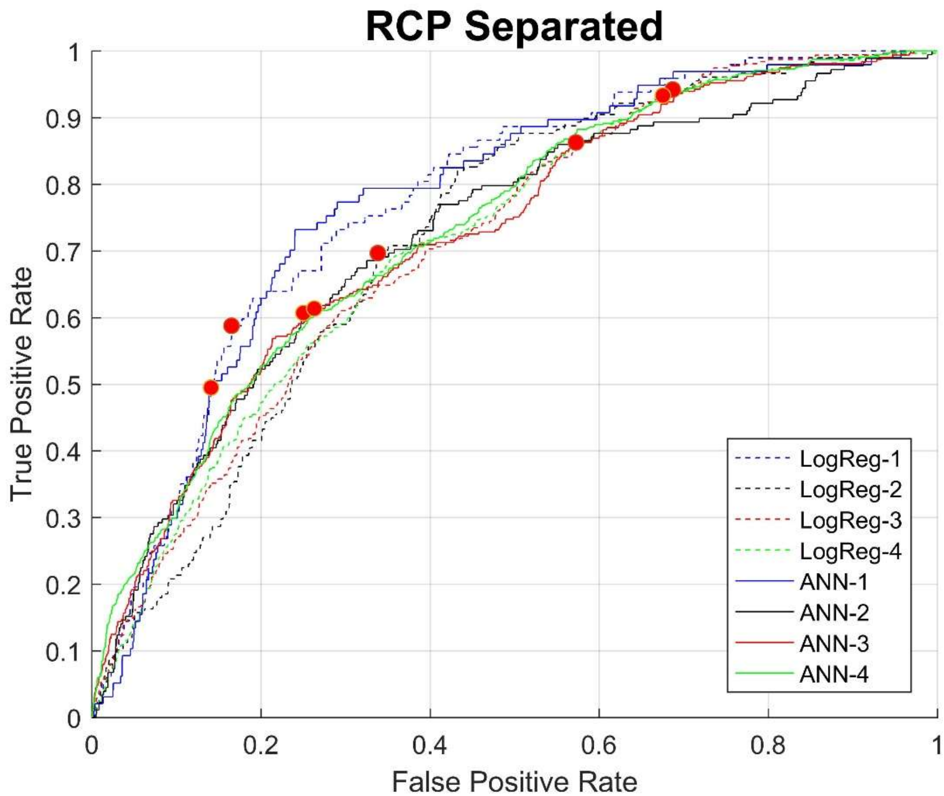


Figure 6.3: Optimal Values shown on ROC Curve Describing RCP Separated

The representation of the optimal points shows a large variety in the location of the points where the model is found to have the least cost. The model differentiating culverts rated as 5 from other culverts captures more than 90% of the culverts with a rating of 4 or less; whereas, the model differentiating culverts rated as 1 from other culverts only captures approximately 50% of these culverts. Ultimately, for the cost analysis to have any significance, actual information on the ratio of cost between incorrectly identifying culverts in good condition and missing culverts in poor condition. Because of the large variation of the percentage of culverts, it would be advantageous to use a method for selecting the threshold limit that provides a more consistent amount of culverts that are prescribed for inspection or rehabilitation.

The second method used to determine the threshold point attempts to maximize the percentage of culverts that were placed in the correct category. By using the cost matrix, the output of the model may categorize all culverts for inspection rendering the model useless. In the case of the logistic regression model and the artificial neural network model, attempting to use the cost matrix as a method for determining the optimal threshold point was ineffective as the model set the threshold point at 0 false positives and 0 true positives. Because each of the models behave differently, setting a single threshold in terms of a percent of culverts is unlikely to serve each of the culvert types and output categories well. Imposing realistic limits on the amount of culverts prescribed for inspection was important to the feasibility of the model. These final model modifications and thresholds are set for each of the six culvert types and ten output categories by using the results of the likelihood function. Using this result allows for the best separation of the data and is equivalent to employing a cost matrix valuing the false positive and false negative terms equally. The overestimation of a culvert's output rating can be corrected for by fitting the observed output versus the predicted output to a regression. This step was most easily done after the composite score was calculated as it meant the user only has to deal with a single value.

Preliminary Conclusions

The distribution of most effective models clearly follows the general rule that more data points (culverts) requires a model with more input variables. In cases where the number of observed culverts were smaller, models that utilized fewer input variables were more successful. This trend, illustrated in **Figure 6.4**, can be shown with a logarithmic relationship for logistic regression models. This conclusion helped to minimize the time spent testing future combinations of input variables for logistic regressions. Future combinations with more input variables could only be tested on RCP culverts, while combinations with fewer inputs could be tested on HDPE and CAP culverts. CMP, masonry, and mixed/other culverts would likely be tested for all additional models as their dependence on the amount of input variables varied more with the type of output that was being predicted. There were no such relationships present in the results of the artificial neural network models. In addition, there were no relationships found between the number of neurons used to determine the final output ratings and the number of inputs in the final model.

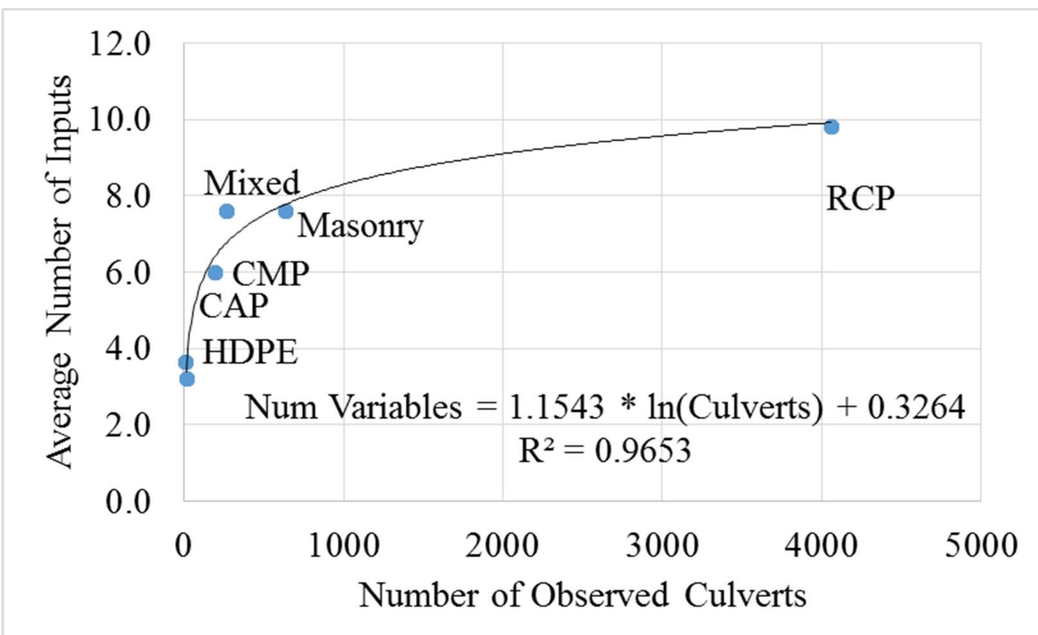


Figure 6.4: Relationship between Observed Culverts and Average Number of Inputs

In a comparison of the performance measures, there was almost no matches in the best combinations between the mean squared error performance indicator and the area under the ROC curve indicator. Only two of the sixty models (3.33%) found the same combinations of input variables to have combination of inputs yield the best model for both mean squared error and area under the ROC curve, because the two performance measures are based on fundamentally different principles. The mean squared error attempts to find the model that creates the closest error for each individual culvert based on a continuous scale. Because the data represented by the SCDOT database has culverts with average ratings above four, the data is skewed toward the higher rated culverts. With this information, the mean squared error performance based models are more likely to predict higher ratings in an effort to reduce overall error. Models based on the area under the ROC curve are viewed as more effective when they can sort the culverts into discrete categories 1-5. The purpose of these models is more in line with the performance characteristics of ROC curves. Ranking the culverts and identifying those culverts in most need of assessment was more important than correctly predicting the rating of culverts, especially those culverts in better condition.

CHAPTER SEVEN

Model Analysis

General Effect of Input Variables

Despite the complexities in determining the assessment rating of culverts using logistic regressions and artificial neural networks, conclusions can be made from the coefficients of the model. In the case of the logistic regression, the influence of each input variable, whether positive or negative can be tracked through these coefficients. In total, 15 unique input variables in the various combinations for each of the logistic regression and artificial neural network models. For each of the inputs their impact on a specific output variable can be either positive, negative, or neutral. The complexity of the problem increases in that each input variable can have a defined impact over only portion of the spectrum of assessment values 1-5. A specific input may significantly impact the decline of a culvert from a rating of 5 to 4, but it may have no effect on the deterioration from 2 to 1. In the case of the dummy variables, this becomes problematic as each coefficient only addresses the binary nature of a single quantifier. Once all of the beta values were determined for each of the six culvert types, it could be used to draw conclusions about each variables contribution to the output variables. For example, a coefficient value of 1.25 for the input variable pH would correspond to an increase in the culvert rating of exp(1.25) or 3.49 for each unit increase in pH with all else equal.

From this information, there were several trends that could be observed for each of the logistic regression models. Each of the trends fell into one of four categories. These trends are also illustrated in **Figure 7.1**.

- Trend 1: As culvert deteriorates, impact of variable decreases*
- Trend 2: As culvert deteriorates, impact of variable increases*
- Trend 3: Input has little effect on variable**
- Trend 4: Impact of variable remains constant as culvert deteriorates

*These trends can have a positive or negative effect on variables

**Because input range changes based on the type of input, a lower value may be misleading (a unit increase may be more significant in pH as compared to a unit increase in precipitation)

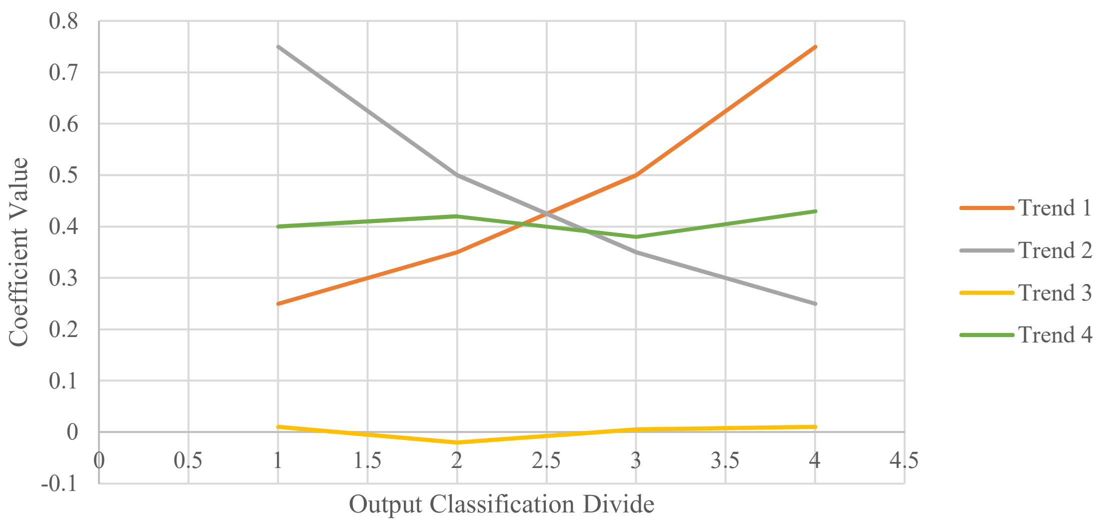


Figure 7.1: Trend Types for Input Coefficients of Logistic Regression Models

The trend of each input variable was assigned for all inputs of each model. There were a total of 10 trend classifications for each input variable as trends 1, 2, and 3 could be considered positive or negative based on the value of the coefficient. With each variable categorized, the general effect of the input variables could be shown to be positive, negative, or having small effects on the output. An attempt was then made to understand these effects and determine if they are in line with assumptions and practices common to design and maintenance of culverts.

The four primary variables that were mapped to each culvert and used in most models were pH, runoff coefficient, temperature, and precipitation. **Figure 7.2** captures the general effect of these variables on the outputs of the model. In these figures, which aim to capture the generalized effect of an input variable on all output variables, the positive and negative effects must be interpreted in terms of the equation that governs the prediction of the output variable.

$$\ln\frac{P(\text{Output}\leq k)}{P(\text{Output}>k)}=\beta_0+\beta_1X_1+\beta_2X_2+\ldots+\beta_nX_n \quad \text{for } k=1,2,3,4 \qquad \text{(Eq 7.1)}$$

In this equation a positive value of β increases the relative probability of the output variable being less than the classification in question (1, 2, 3 or 4). Through this example, a variable indicated as having a negative beta value increases the probability that a given output variable is greater than the threshold. In examining the generalizations of the impacts of the primary variables, most of these variables are shown to have a negative value. Consequently, a decrease in the value for these variables would correspond to an increase in the probability that the culvert is in better condition than the indication point.

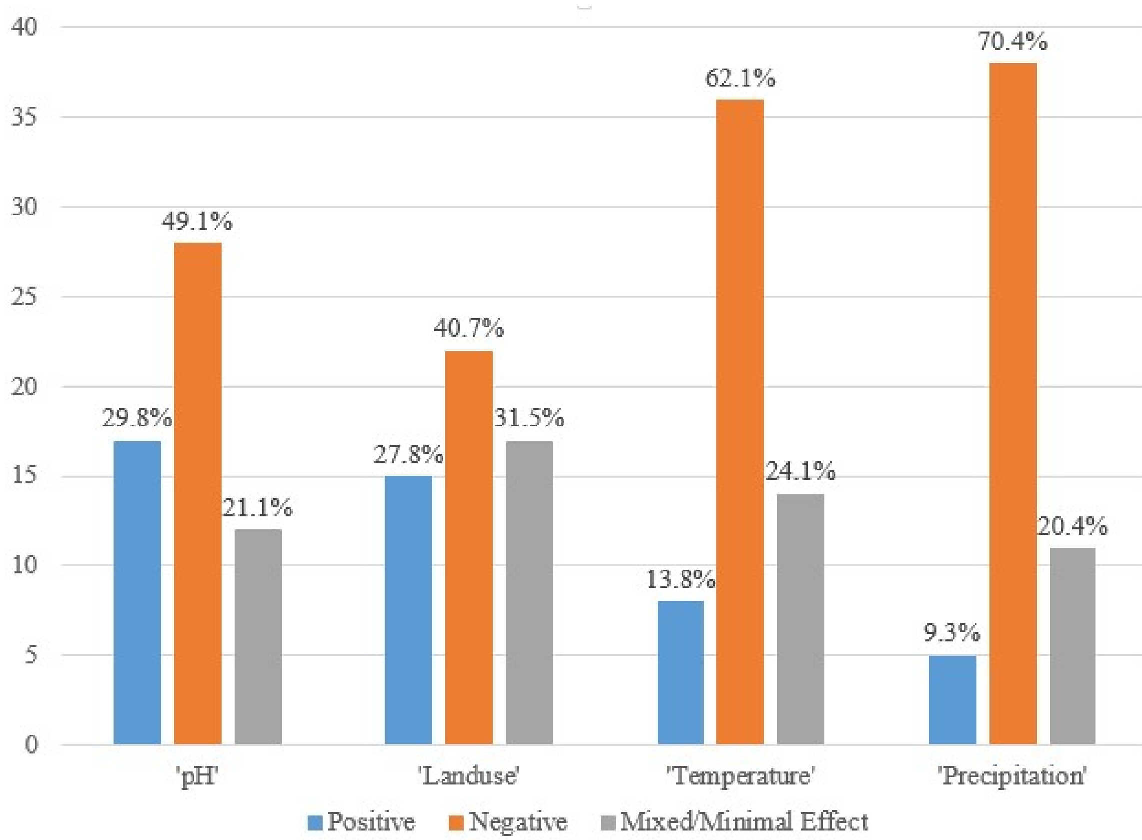


Figure 7.2: Distribution of Effect of Primary Input Variables

It is important to determine if the negative values for pH, runoff coefficient, temperature, and precipitation follow the general logic of the effects of these variables. Proving that an increase in the pH would help a culverts rating, especially its corrosion rating, follows the logic that more acidic water is worse for a culvert's health. Similarly, a negative value associated with the temperature coefficient, particularly in structural related models indicates that the places in South Carolina that are colder and more susceptible to freeze and thaw cycles, would have a negative effect on the culvert's output ratings. These trends can also be observed in a graph of the predicted outputs as a function of the primary input variables.

The negative values associated with the input variables of runoff coefficient and precipitation are not as easily explained with intuition. In the case of both runoff coefficient and precipitation, an increase in these inputs would mean an increase in demand on the culvert. While this effect can be explained for some output variables like blockage and vegetation where an increase in the amount of water would decrease the likelihood for excess vegetation, sedimentation, and culvert blockage, other output variables would not logically benefit from an increased amount of water. Alignment, cracking, and erosion would logically see a reduction in output rating with an increase in the precipitation and runoff coefficient when examined in a global sense. It was important to note that the life cycle of a culvert is dependent on the localized conditions that effect the demand, and the input variables used to predict the output capture a localized effect of each input variable on the culvert.

These general effect were confirmed with graphs isolating a culvert's predicted output score were plotting against each primary variable. To give reference, the actual distribution of ratings was shown in red, while the predicted rating was shown in red (**Figure 7.3**).

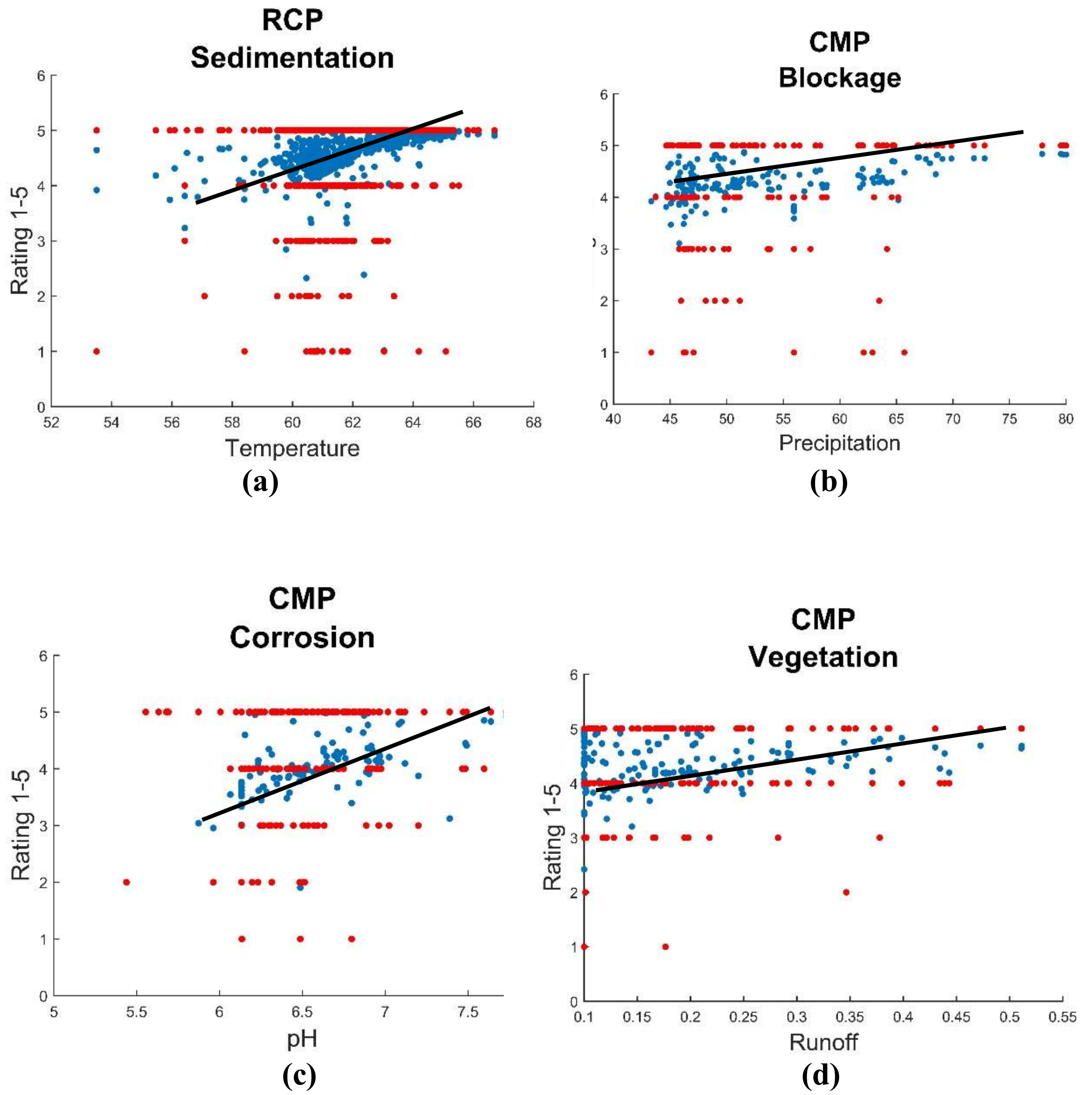


Figure 7.3: Demonstration of Negative Coefficients and Positive Impact

Composite Output Rating Analysis

Once the ten output categories had been calculated based on the logistic regression and the artificial neural network models, they could be compiled into one rating based on surveys conducted to state Departments of Transportation (DOT). The composite ratings for the RCP-like and CMP-like culverts could then be compared to the similarly calculated observed ratings through the SCDOT assessments. Using the relative importance of each of the six defects considered to be important gives a final composite score. This composite score could be compared to a calculated composite score for each culvert in the SCDOT culvert assessment database and corrected using an error term. For each model type and each of the three possible composite score methods (**Table 7.1**). The primary performance measure of the model's accuracy was the coefficient of determination (R^2). The figures illustrating the calculation of these coefficients is shown in Appendix B.

Table 7.1: Coefficient of Determination (R^2)

		RCP	CMP	CAP	HDPE	Masonry	Mixed
Neural Network	**Average**	0.252	0.562	0.090	0.687	0.569	0.519
	DOT Est 1	0.217	0.550	0.100	0.668	0.476	0.490
	DOT Est 2	0.246	0.566	0.071	0.656	0.551	0.509
Logistic Regression	**Average**	0.132	0.334	0.612	0.753	0.344	0.279
	DOT Est 1	0.132	0.349	0.536	0.856	0.280	0.373
	DOT Est 2	0.135	0.340	0.613	0.711	0.340	0.250

The first observation from the composite score analysis was that each culvert type had a significant advantage using one model type versus another. For RCP, CMP, masonry, and mixed/other culverts, the artificial neural network model proved to produce better results. For the CAP and HDPE models, the logistic regression model proved to explain more of the variation. A possible reason for this occurrence is the lack of data that can be found in the CAP and HDPE categories. When the amount of information was less, the simplest model did the best job of explaining the causes and effects of the input variables. The linear addition of the input variables proved to be the best way to describe the condition of the culvert when only a few culverts were available. This phenomenon may also have been the case because all of the data was used to create the logistic regression models. Without any validation of the model with unused data, a significant bias can be introduced when only a few data points exist.

The second observation was that there was no clear method of developing a composite score that proved to be better than the others. For all culvert types except HDPE, the top two methods for determining composite score were within 10% of each other. This could be partially due to the fact that the two DOT estimates for the relative severity of defects showed only slight differences for RCP and CMP culverts. Furthermore, the differences between the DOT estimates and a simple average of the six output variables assumed to be significant were relatively small as well. Moving forward, all three models will be available for the user to select. The user could also input their own set of weighting criteria. In addition, other combinations of the output variables could prove to do a better job at estimating the overall ratings of the culverts, but they may not accurately represent the health of the culvert in question.

A final observation of the composite score analysis was the relatively low magnitude of the coefficient of determination in comparison to previous research. For the culvert type with the most available information, RCP, the coefficient of determination was the worst (0.252). This means that only 25.2% of the variability in the data for RCP culverts is captured by the current model. A possible reason for this poor model could be too much data used to create the model. Because the distribution of the data from the SCDOT Culvert Assessment Database was significantly skewed to the culverts with ratings of 4 and 5, and the model attempts to reduce the amount of total error produced by the regression, the model is biased towards the higher rated culverts.

In models where the distribution of culverts had closer to equal amounts of culverts in each category, the coefficient of determination was higher.

Using the tools available in a regression analysis allows for the error term to be included in the model. When the user inputs a culvert's information, the logistic regression or artificial neural network model will produce an estimate based on the functions that define that particular model. The prediction will then be used in the linear regression analysis to produce a final prediction of the culvert's composite score. In addition to this prediction, the variability in the data will allow for a range of predictions to be made. This range deals with the variability at a specific point in the regression analysis. As shown in **Figure 7.4** representing CMP culverts and a composite scored determined by the DOT defect weighting estimate for CMP culverts, the boundary for the culverts can be seen. The upper and lower boundary look to capture one standard deviation from the mean value predicted by the regression. This additional parameter can serve to allow the user to have an estimate as to the lower and upper bound of the composite score.

Variability in the Models

The distribution of the standard deviation for each model can serve to help understand how well the model captures the data with the single prediction. The larger the standard deviation, the less the single prediction accounts for more of the data. For most of the models and composite score weights the average standard deviation across the spectrum of possible answers (1-5) was between 0.3 and 0.6. In a case where the standard deviation is 0.5, approximately half of the variation is captured in a range of 1.0.

A complete breakdown of the standard deviation associated with each of the composite scores and culvert types is shown in **Table 7.2**. The average standard deviation was determined by finding the standard deviation of equally spaced points from a predicted output of 3 to a predicted output of 5. Because there was much more variability in the model below an estimation of 3 and very few entries, an average of equally spaced points between 1 and 5 would not give an accurate indication of the average standard deviation. The increased variability can be seen where the lines indicating the standard deviation grow farther apart as the predicted value decreases. This is to be expected as there are fewer data points lower on the scale and the models ability to predict them has decreased.

Figure 7.4: CMP Composite Score DOT Estimate 2 with Error Term

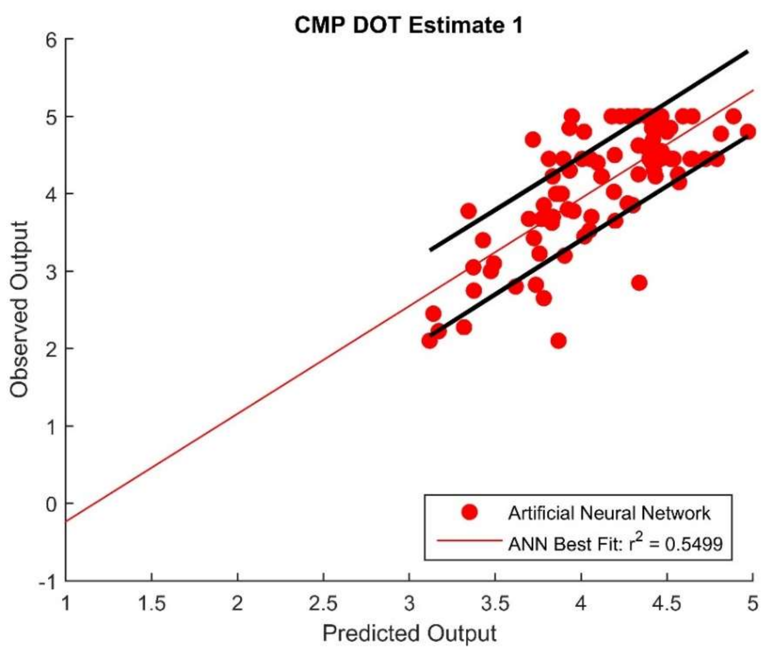


Table 7.2: Standard Deviation for Each Model Type and Composite Weight

		ANN	LogReg
RCP	DOT Est 1 - RCP	0.479	0.500
	DOT Est 2 - CMP	0.503	0.515
	All Equal	0.497	0.514
CMP	DOT Est 1 - RCP	0.524	0.630
	DOT Est 2 - CMP	0.549	0.639
	All Equal	0.512	0.621
CAP	DOT Est 1 - RCP	0.504	0.388
	DOT Est 2 - CMP	0.561	0.483
	All Equal	0.526	0.396
HDPE	DOT Est 1 - RCP	0.643	0.422
	DOT Est 2 - CMP	0.617	0.252
	All Equal	0.697	0.483
Masonry	DOT Est 1 - RCP	0.314	0.376
	DOT Est 2 - CMP	0.339	0.390
	All Equal	0.323	0.379
Mixed	DOT Est 1 - RCP	0.421	0.533
	DOT Est 2 - CMP	0.457	0.529
	All Equal	0.422	0.540

CHAPTER EIGHT

Model Conclusions

Weaknesses of Models

When considering the finalized models, it was important to understand the limitations and weaknesses of its prediction capabilities. The first major weakness of the model was the spatial bias that was created when the mapped input variables were assigned to the culverts. Because these mapped inputs varied spatially using linear interpolation, two culverts that were located very close together could receive nearly identical values for temperature, precipitation, pH, and estimated runoff coefficient. With all other physical properties like culvert type, culvert shape, and dimensions equal, these culverts would likely receive a nearly equal estimate for the output variables. With no additional way to differentiate these culverts such as age, any variation in the ratings of these culverts would not be captured by the model.

In addition to the localized spatial bias, the model may be affected by spatial bias in the global sense. Where models were created with fewer culverts (HDPE and CAP) the model could separate these culverts and assign ratings based entirely on spatial variation illustrated in **Figure 8.1**. In this case, the model would predict the culvert rating based on this spatial bias. Any validation performed on this model shows that the predition capabilities for the model are very poor. This was underscored by the neural network's poor performance on culvert types with fewer data points as the neural network process includes validation.

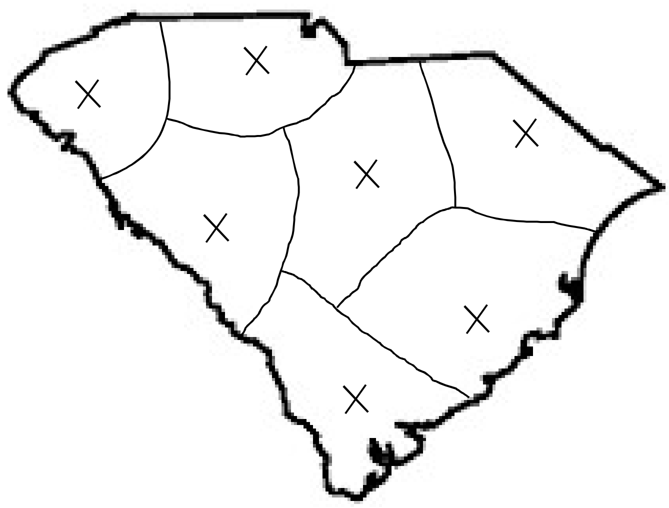


Figure 8.1: Spatial Bias Potential in Models with Fewer Input Culverts

In addition to the spatial bias, there is a bias in the model towards the highly rated culverts. Because the distribution of culvert output ratings was significantly skewed towards the higher rated culverts (**Table 8.1**). When using models that incorporate all data or a percent of the entire data, the model sought to maximize the performance indicators. With more of the data receiving higher rating, the model prioritizes accurately estimating these data points at the expense of over-predicting the lower rated culverts. Some of this bias is removed by emphasizing the ROC curves and the models ability to separate these culverts from the higher rated culverts, but the bias is clearly still evident in the analysis of the composite score comparisons (**Figures** in Appendix B).

Table 8.1: Distribution of Culvert Ratings in SCDOT Culvert Database

Output Rating	Percent
1	2.2%
2	2.3%
3	6.9%
4	18.7%
5	69.8%

As previously documeted some of the output categories have no rankings. Because the model has not been exposed to a culvert with an output rating in these categories, unless significant values for the major input variables are achieved, it is unlikely that the model will ever produce a culvert with an output rating equivalent to the missing culvert output ratings. Futhermore, the values for the site specific variables are capped at a minimum and maximum value, making the likelihood that the model would produce a rating outside the range of those currently seen in the culvert database even smaller.

Another weakness to the model that needs to be addressed is the method for which the value of the output variable was determined. Because all of the output categories were taken into account to produce the final output score for each of the ten categories, each of the outputs were considered to have equal weight with respect to the health of the culvert. For example, the cracked output score for each culvert was a combination of seven different categories; three addressed the inlet, three addressed the outlet, and one addressed the rating of the barrel. For this case, a poor cracking rating for the inlet and outlet are significantly less severe than a poor rating for the barrel of the culvert. Because the minimum output rating for all seven of these categories was taken to be the respresentation of the cracking output for the entire culvert, a bias could be placed on certain culverts in the existing database. If the defects ranked by the culvert database were given a significance based on the area of the culvert that they addressed, a more accurate representation of the culvert's output ratings could be produced and a potentially more accurate model could be used. It is important to note that the accuracy of the model is significantly dependent on the accuracy of the database used to create the models. In addition, the defects predicted by the model may be misleading as all culvert types receive a predicted score for each of the output categories. This means that CMP culverts will receive a cracking score despite the fact that cracking is not likely to occur in these types of culverts. This weakness in the model is overcome by a knowledgable user that interprets the model's output to best serve their purpose.

A final significant weakness to the model in its current state is the lack of a time-dependent variable. Because the input variables all remain constant, the model produces a prediction that would remain the same if the model was used again later. Without an input variable that gives some indication of time, the model is not a deterioration model, it is simply a predictive model. Limited age information was provided for 29 total culverts and the associated analysis of this information is presented in Appendix C. This weakness could be corrected if the model was updated in the future for a similar database of culverts. If historical data on the rainfall, temperature, pH, and land cover were updated periodically, it may give the model a chance to predict these variables more accurately. In addition, if the same culvert was rated more than once over a period of time, a measure of the deterioroation over time could be achieved.

Strengths and Benefits of Models

Both the logistic regression and artificial neural network models aimed to predict the ratings of each of the output categories. Because the model was separated into individual models aimed at capturing the response of culvert to a single output score, it can be used to assess what culverts in the state of South Carolina have a poor prediction rating for only specific output categories. For example, it may be of concern only those culverts in South Carolina that have blockage, sedimentation, or vegetation issues. Using the model may allow for the SCDOT to identify those culverts that may be in need of simple repair so that further problems do not develop and decrease the rating of the culvert. In addition, the model can be used to determine where in South Carolina, certain defects are more common or predicted to be more of a concern.

Another advantage of the culvert prediction model is that it only requires information about the physical characteristics and location of the culvert. Using only these characteristics allows the user to predict a rating for the culvert without any field inspection or knowledge of the site specific characteristics of the culvert. The model allows the user to rank culverts in terms of importance using only these parameters.

In the final model, both the artificial neural network model and the logistic regression model will be available for the user to select and use. However, based solely on the coefficient of determination performance measure, one model is clearly better than the other for each of the culvert type (**Table 8.2**). The flexibility of using one set of models versus another for a given culvert type also allows for some of the error introduced by spatial bias or a lack of complexity in the logistic regression model to be handled by the other model type.

Table 8.2: Breakdown of More Accurate Model

Model Type	More Accurate Model
RCP	ANN
CMP	ANN
CAP	LogReg
HDPE	LogReg
Masonry	ANN
Mixed/Other	ANN

Modifications to Future Models

For the model to continue to improve in its capabilities to predict the output of culverts, modifications and updates are necessary. A continued analysis to the impact of the age of a culvert would allow for these models to be applied to all culvert types and likely produce more accurate models. Implementing the model would only be possible if the age of future culverts whose condition was desired also had a known installation date. With these models would come an expected increase in accuracy as well as a prolonged useful life of the model. If the model could take into account a time-dependent variable, the model is no longer static and could produce more meaningful results in the future without an update in the parameters of each individual model.

Another important modification to the current model that could bring about an increase in the performance would be using different portions of the data to train the original estimates for the model coefficients. This would apply mostly to the models with a large amount of data. In these cases it may be advantageous to use equal or nearly equal amounts of data from each output category. Because nearly 90% of the data has an output score of either 4 or 5, the bias towards this data is significant, but likely correctable. By forcing the model to treat each output equally, it may be more likely to capture the true trends in the data and deterioration of culverts.

APPENDICES

Appendix A

ROC Curves for Each Model

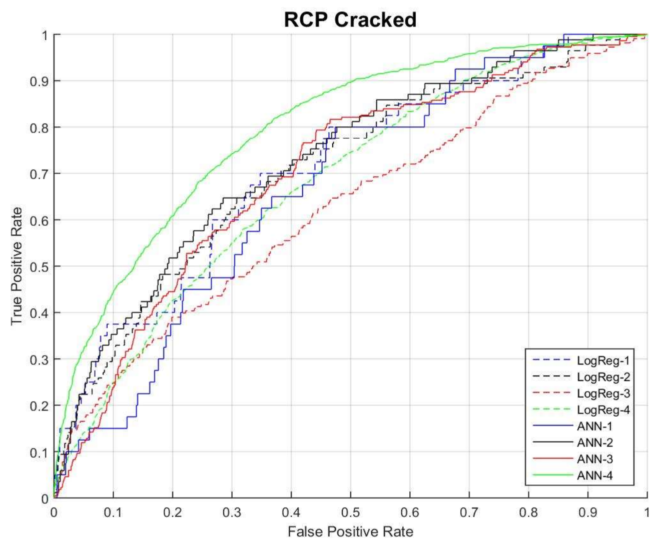


Figure A-1: ROC Curve for RCP Cracking

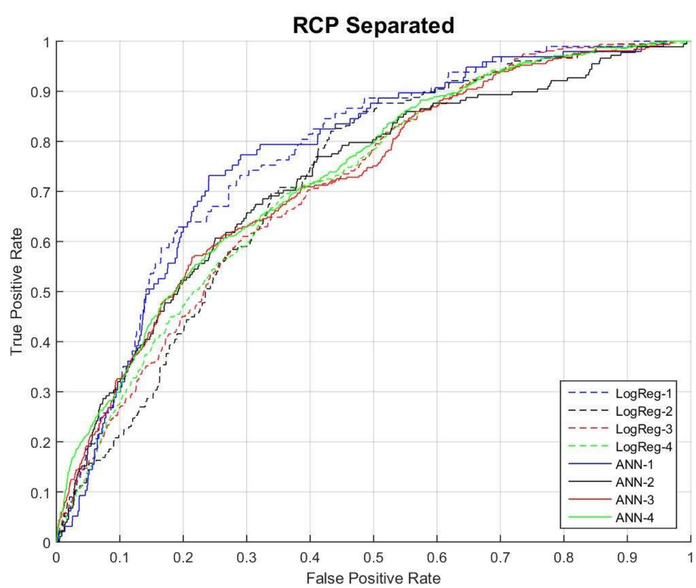


Figure A-2: ROC Curve for RCP Separated

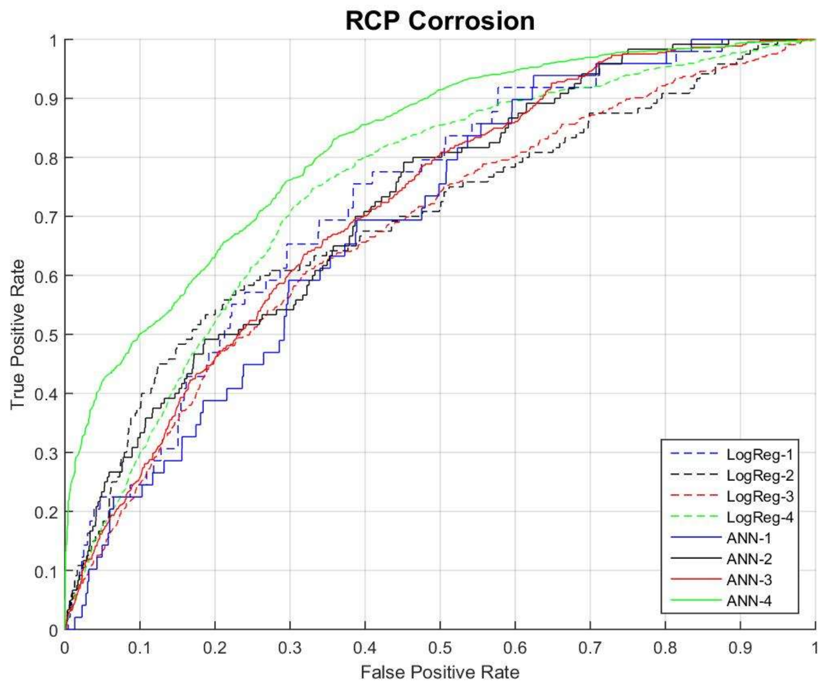


Figure A-3: ROC Curve for RCP Corrosion

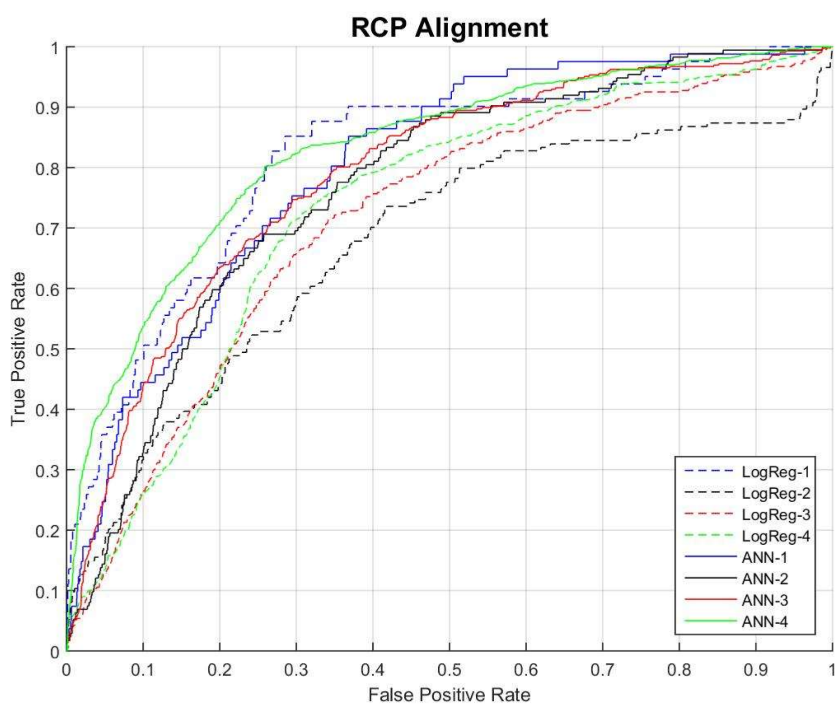


Figure A-4: ROC Curve for RCP Alignment

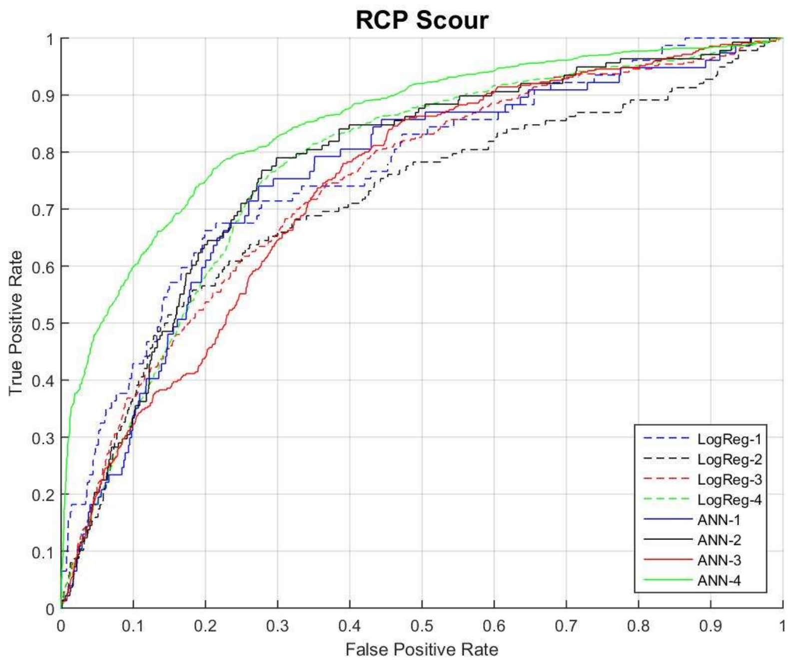


Figure A-5: ROC Curve for RCP Scour

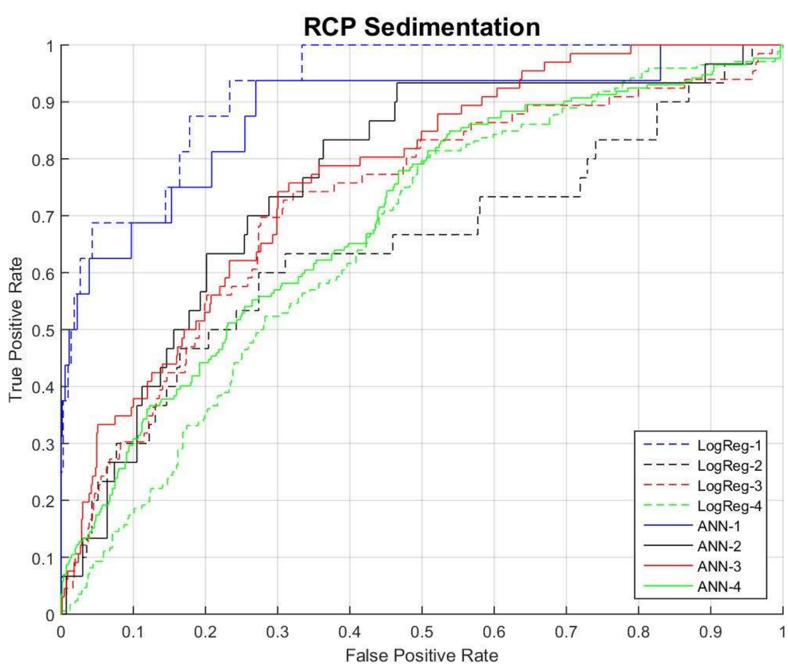


Figure A-6: ROC Curve for RCP Sedimentation

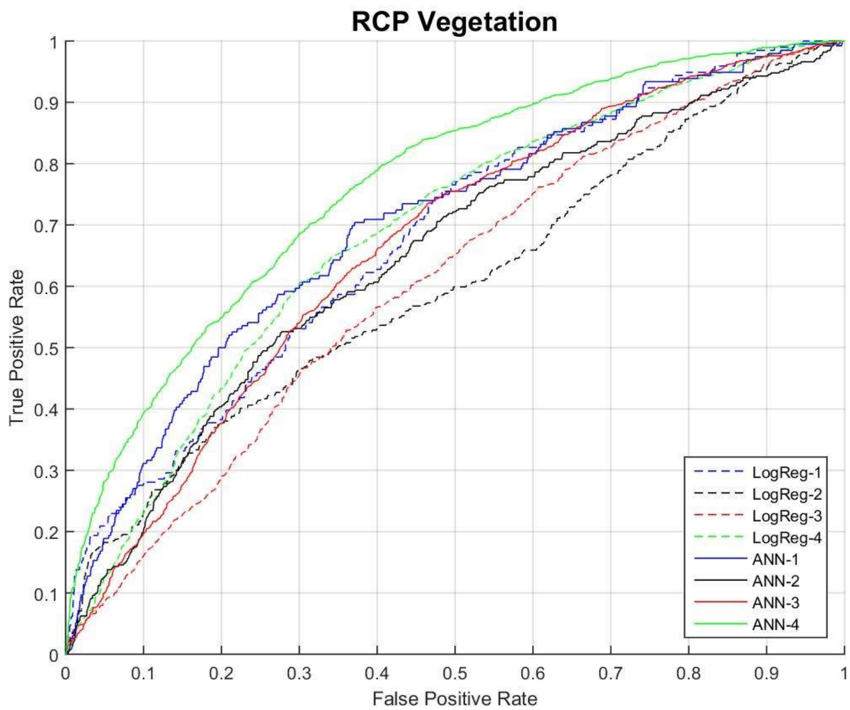


Figure A-7: ROC Curve for RCP Vegetation

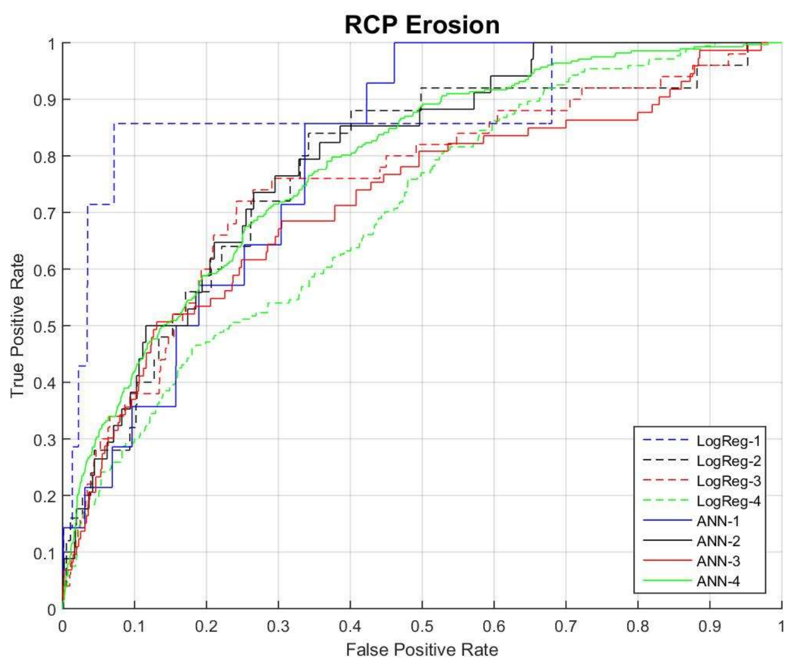


Figure A-8: ROC Curve for RCP Erosion

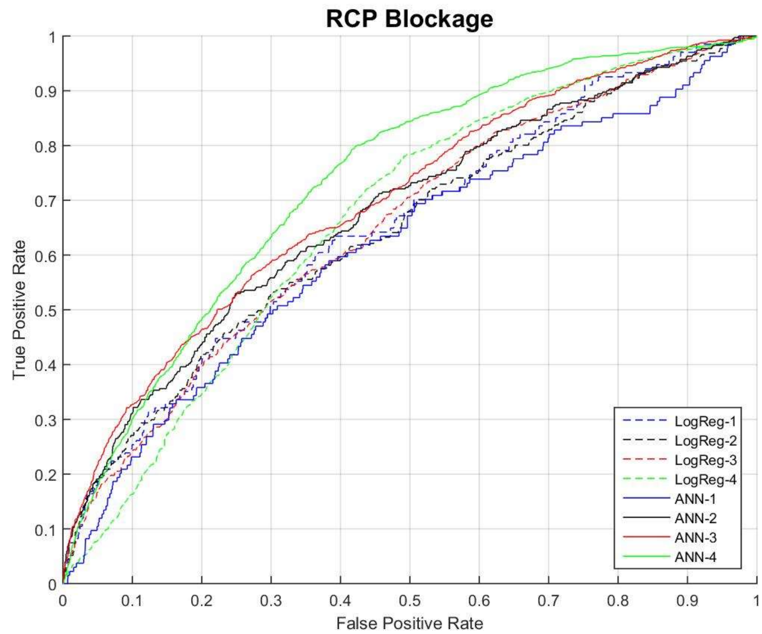


Figure A-9: ROC Curve for RCP Blockage

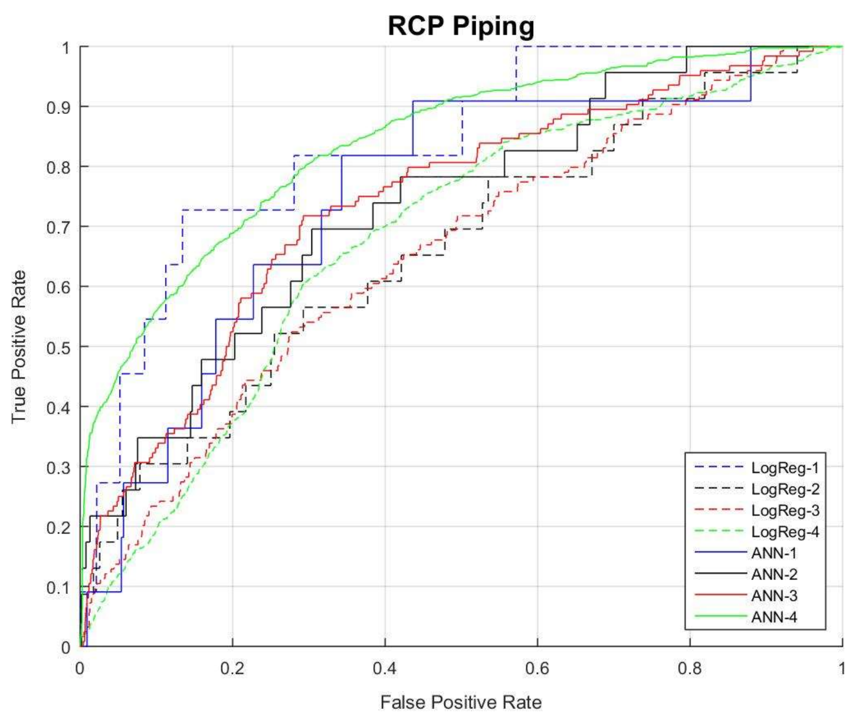


Figure A-10: ROC Curve for RCP Piping

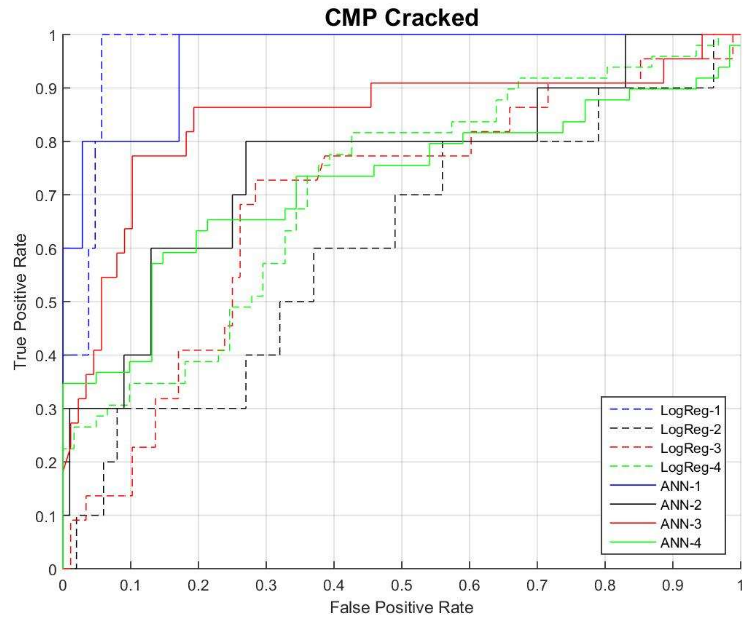


Figure A-11: ROC Curve for CMP Cracking

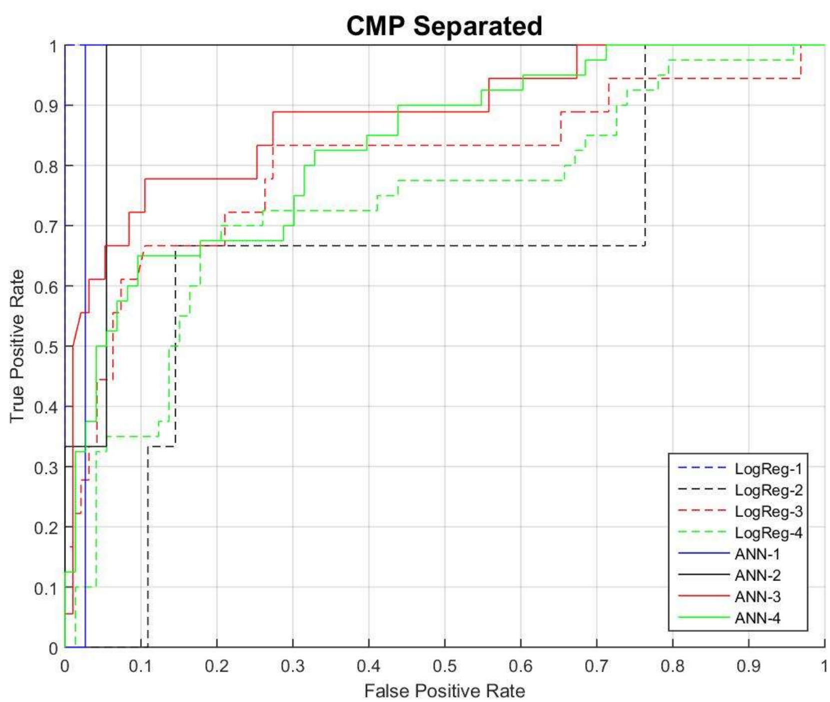


Figure A-12: ROC Curve for CMP Separated

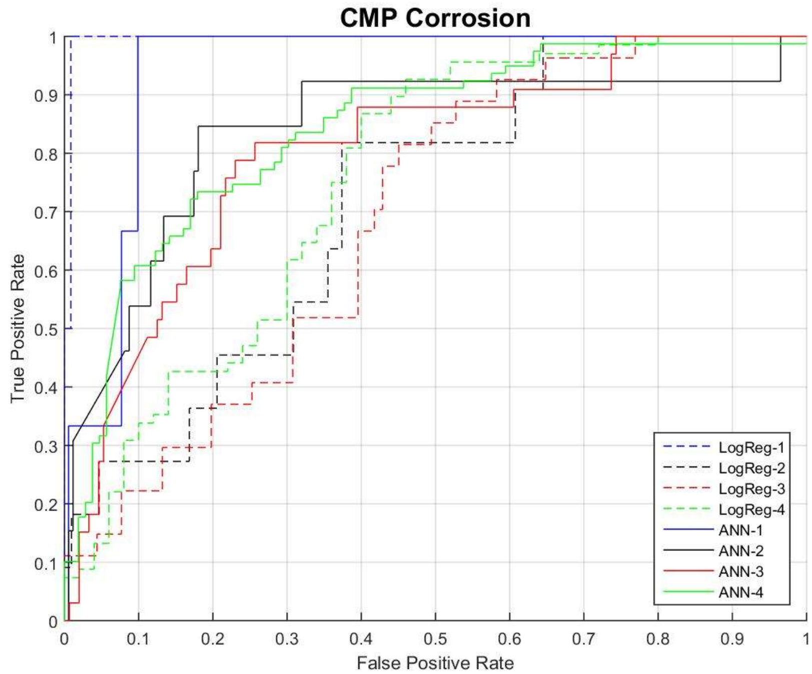


Figure A-13: ROC Curve for CMP Corrosion

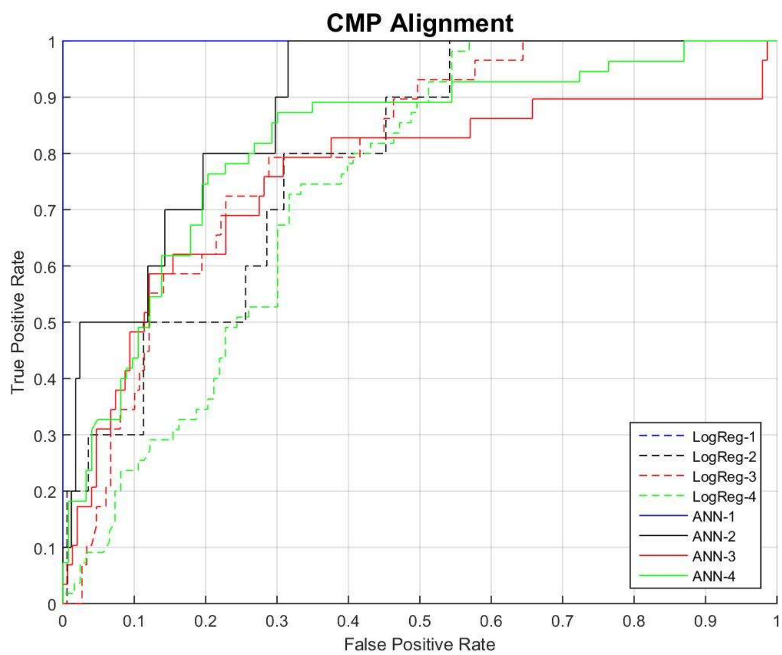


Figure A-14: ROC Curve for CMP Alignment

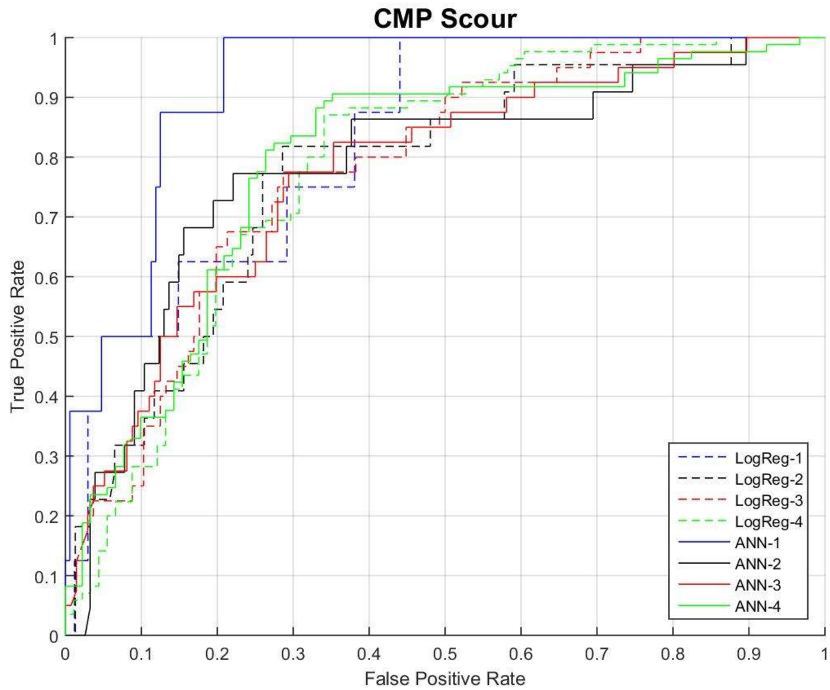


Figure A-15: ROC Curve for CMP Scour

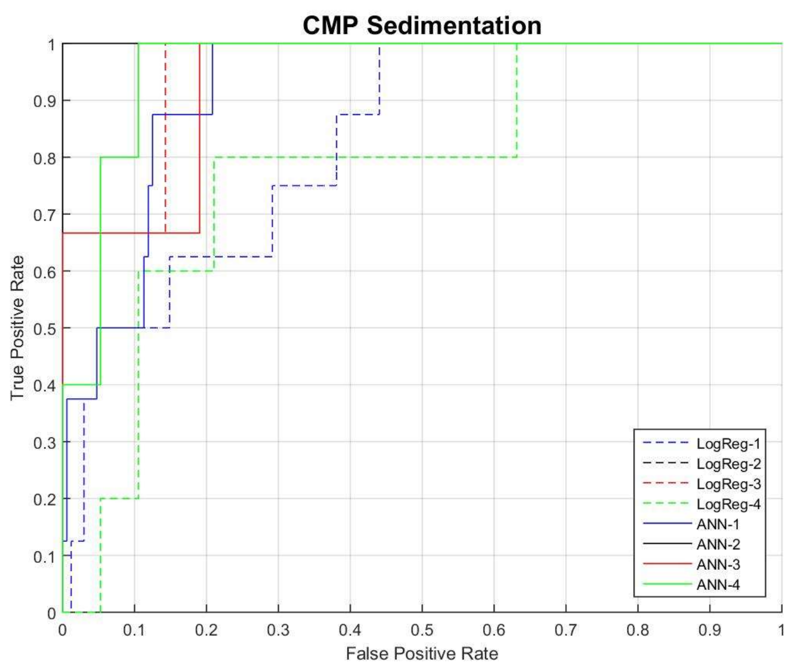


Figure A-16: ROC Curve for CMP Sedimentation

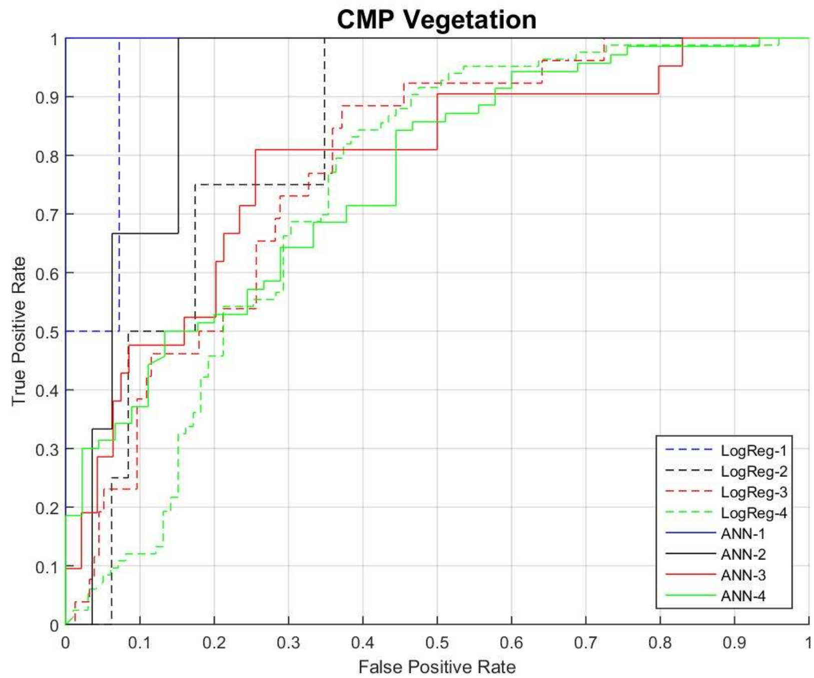


Figure A-17: ROC Curve for CMP Vegetation

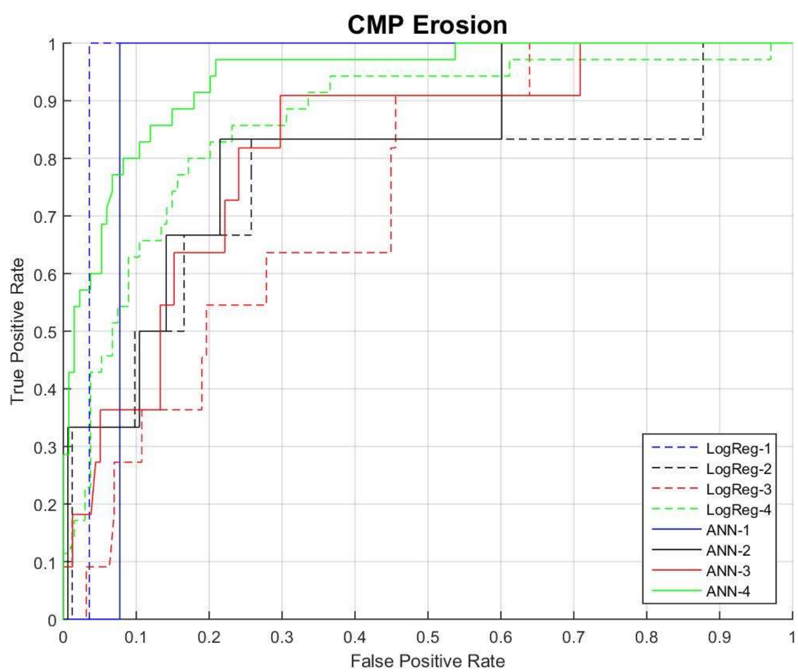


Figure A-18: ROC Curve for CMP Erosion

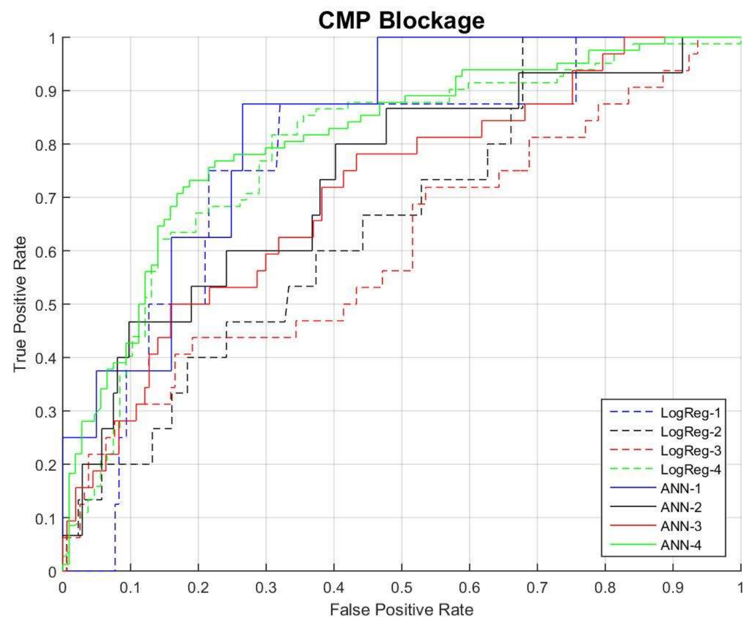


Figure A-19: ROC Curve for CMP Blockage

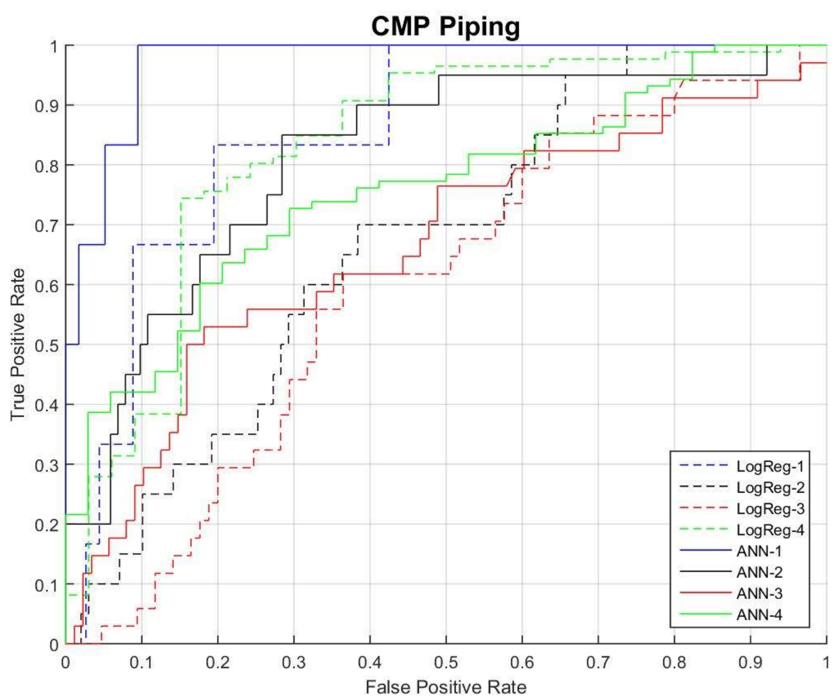


Figure A-20: ROC Curve for CMP Piping

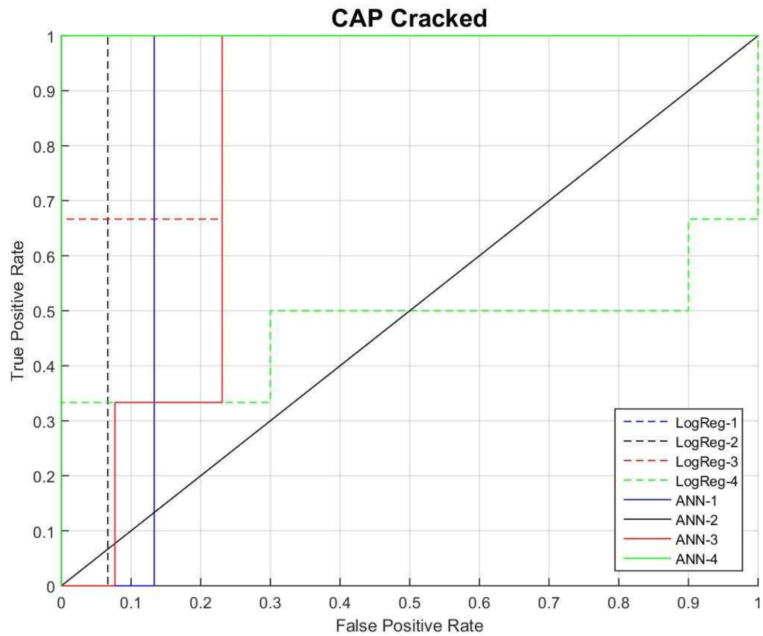


Figure A-21: ROC Curve for CAP Cracked

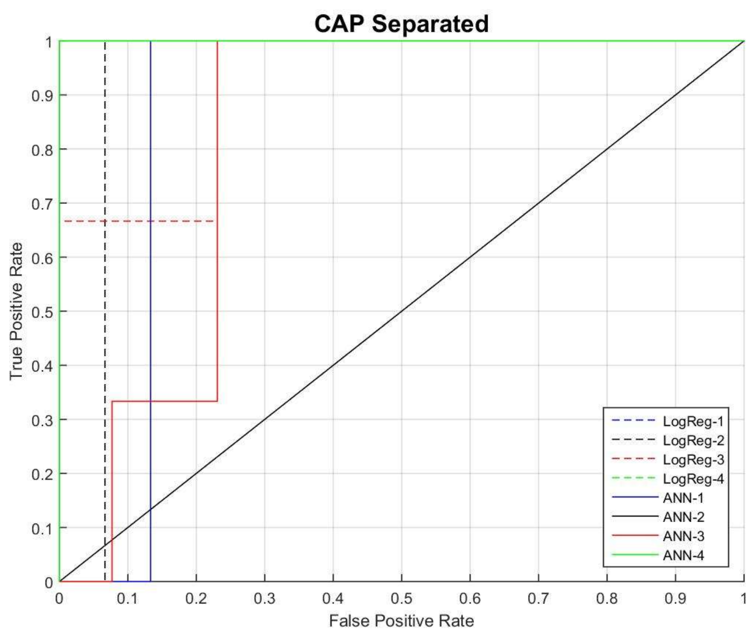


Figure A-22: ROC Curve for CAP Separated

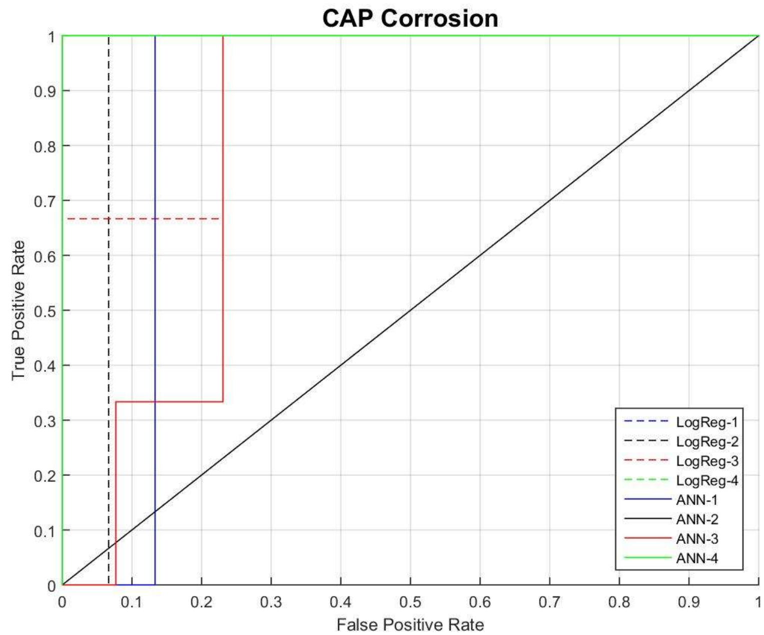


Figure A-23: ROC Curve for CAP Corrosion

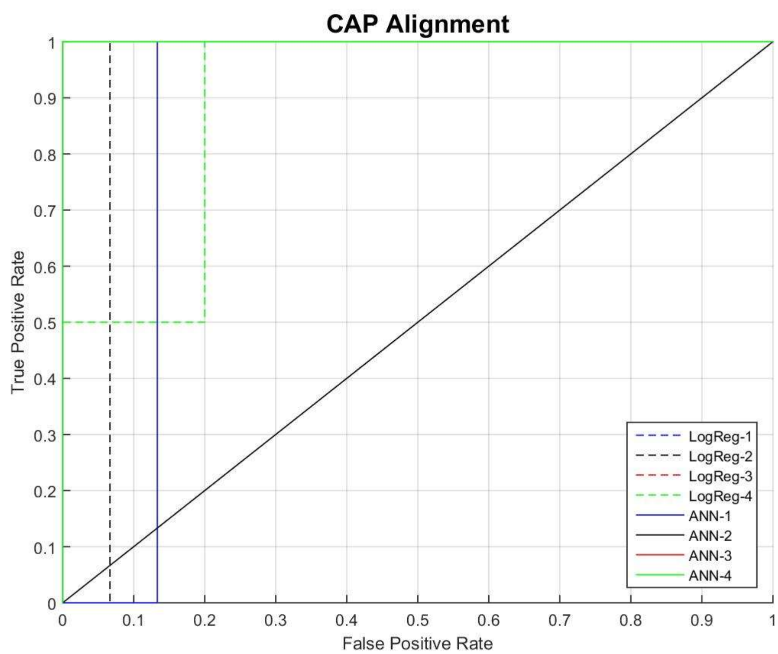


Figure A-24: ROC Curve for CAP Alignment

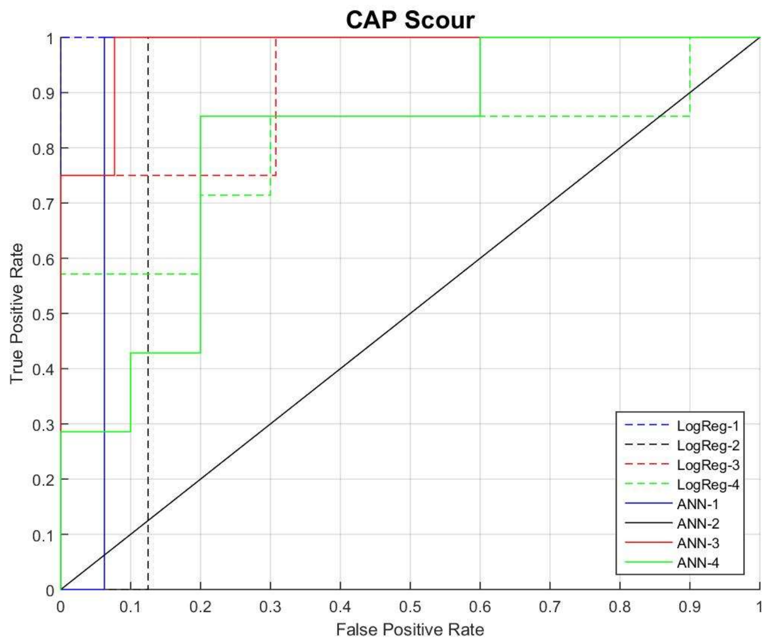


Figure A-25: ROC Curve for CAP Scour

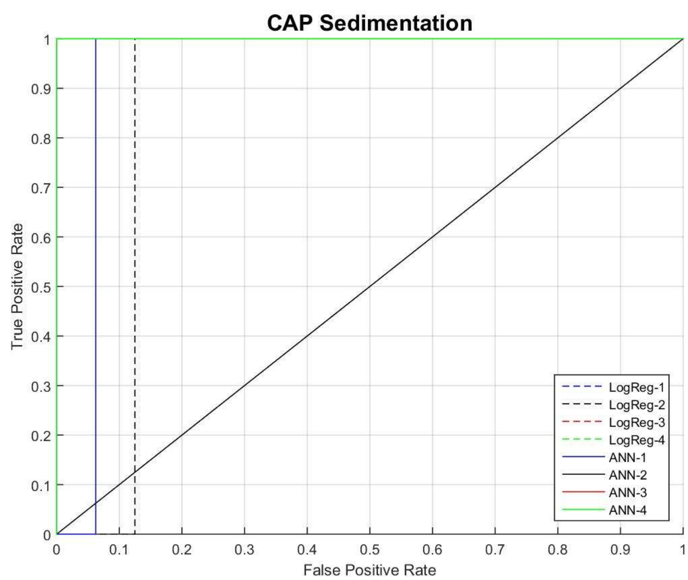


Figure A-26: ROC Curve for CAP Sedimentation

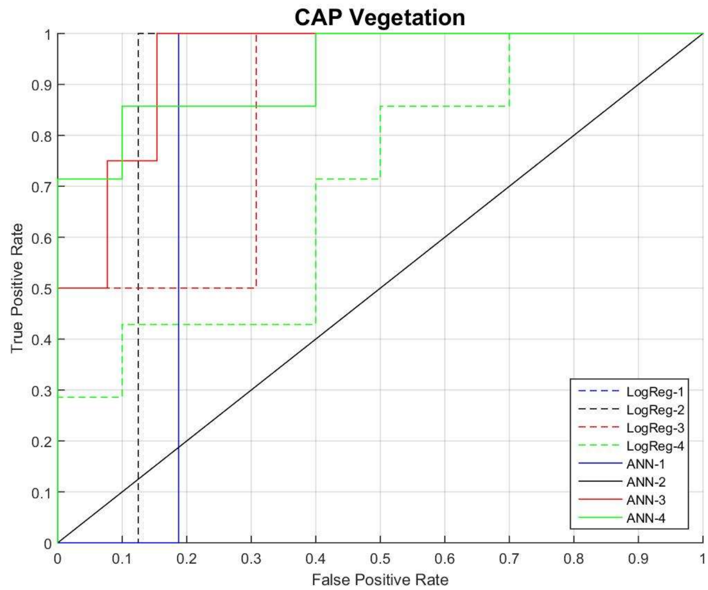


Figure A-27: ROC Curve for CAP Vegetation

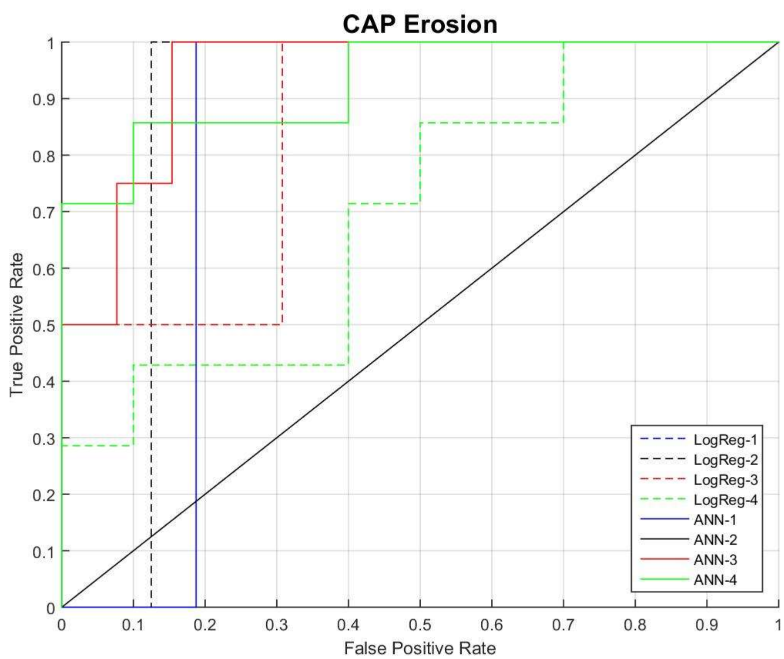


Figure A-28: ROC Curve for CAP Erosion

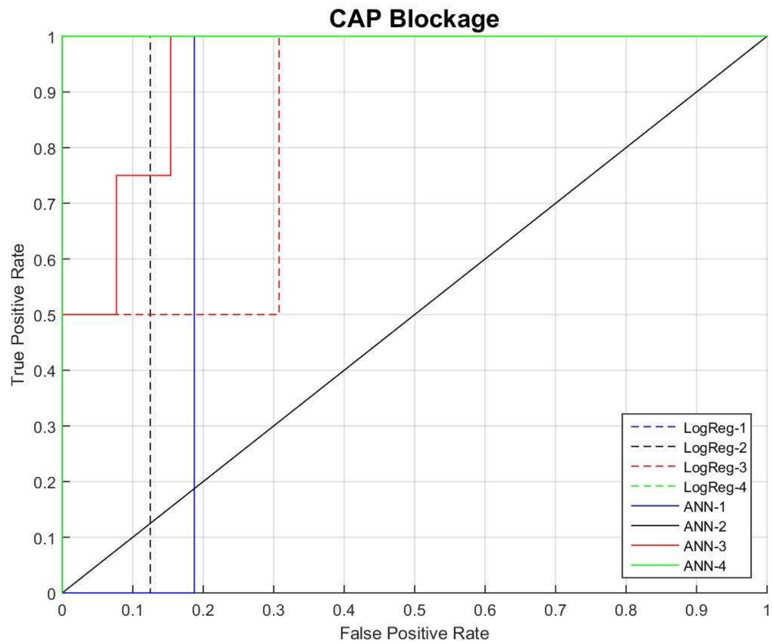


Figure A-29: ROC Curve for CAP Blockage

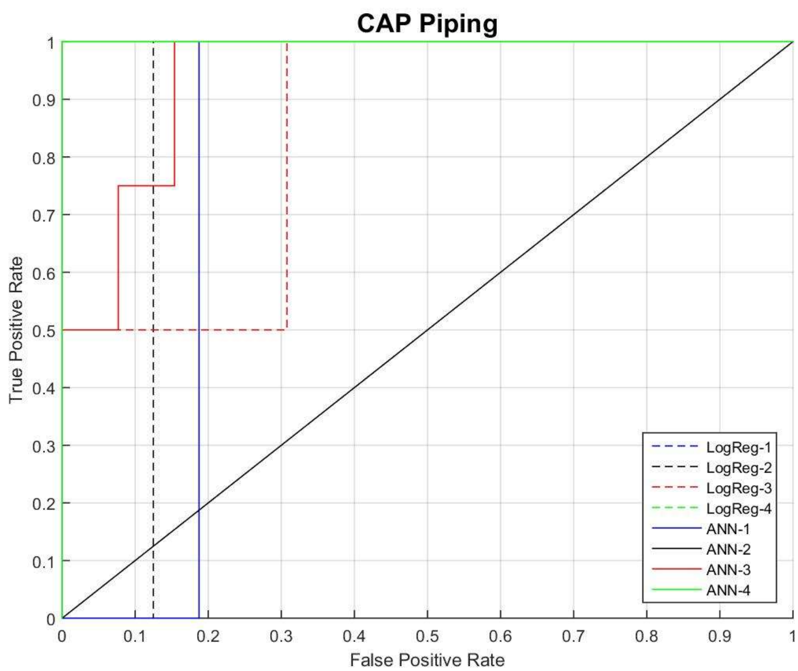


Figure A-30: ROC Curve for CAP Piping

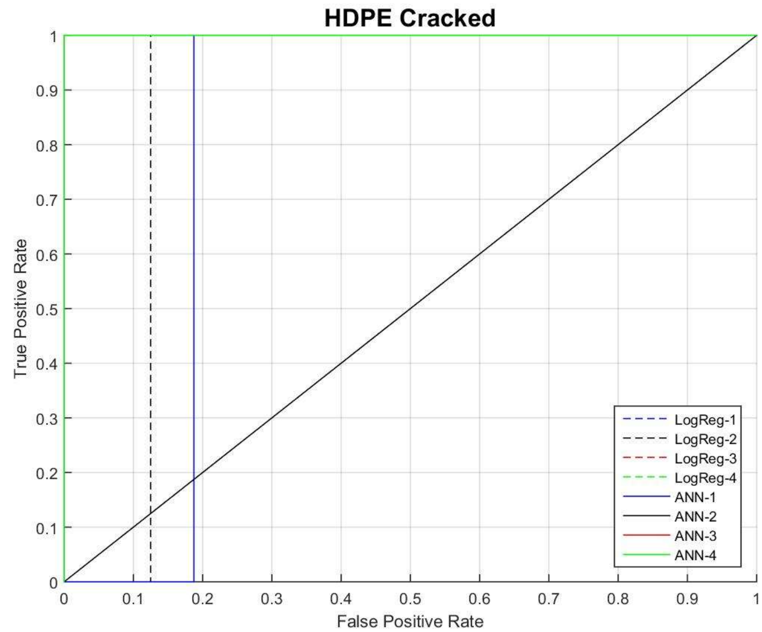


Figure A-31: ROC Curve for HDPE Cracked

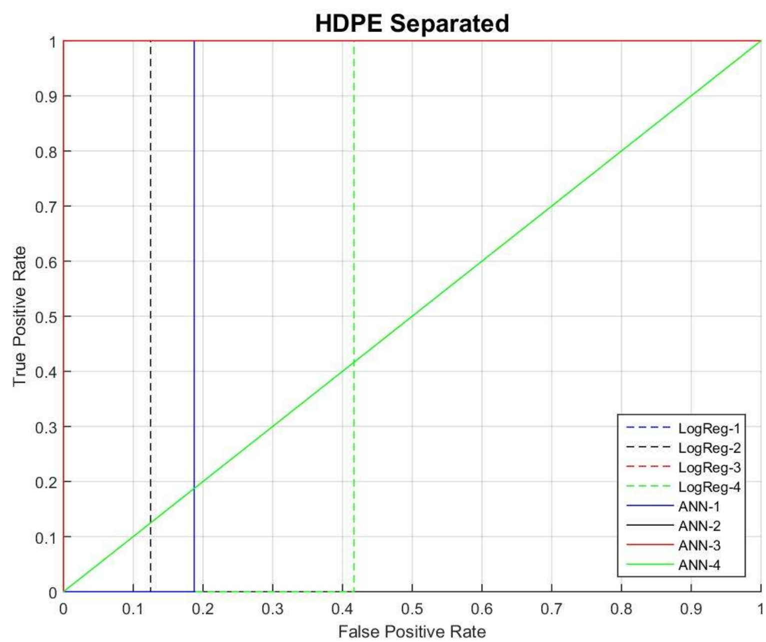


Figure A-32: ROC Curve for HDPE Separated

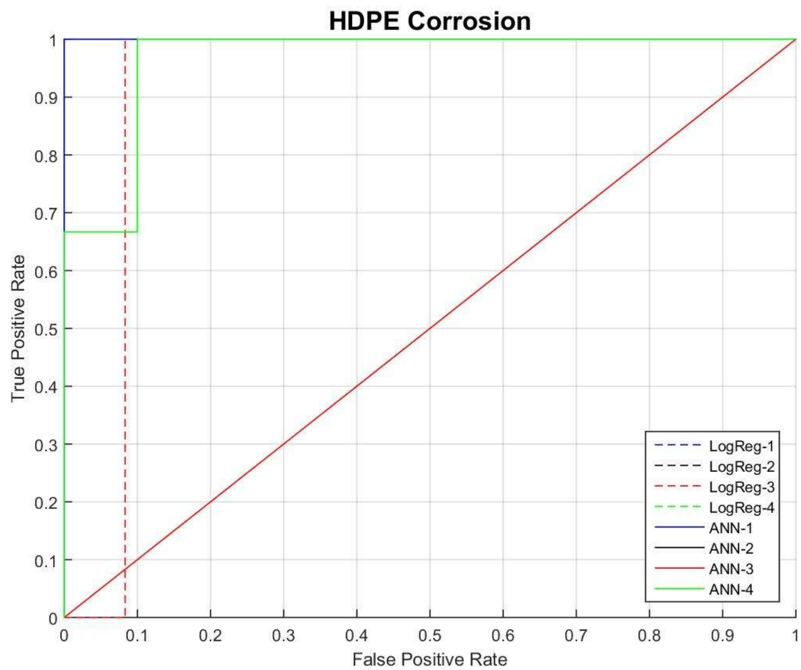


Figure A-33: ROC Curve for HDPE Corrosion

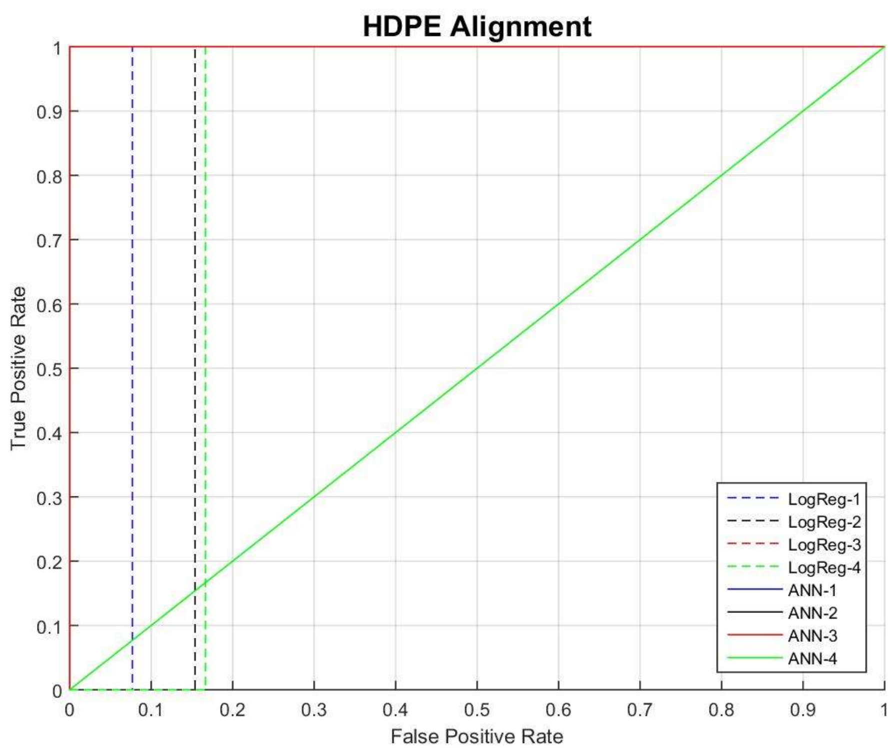


Figure A-34: ROC Curve for HDPE Alignment

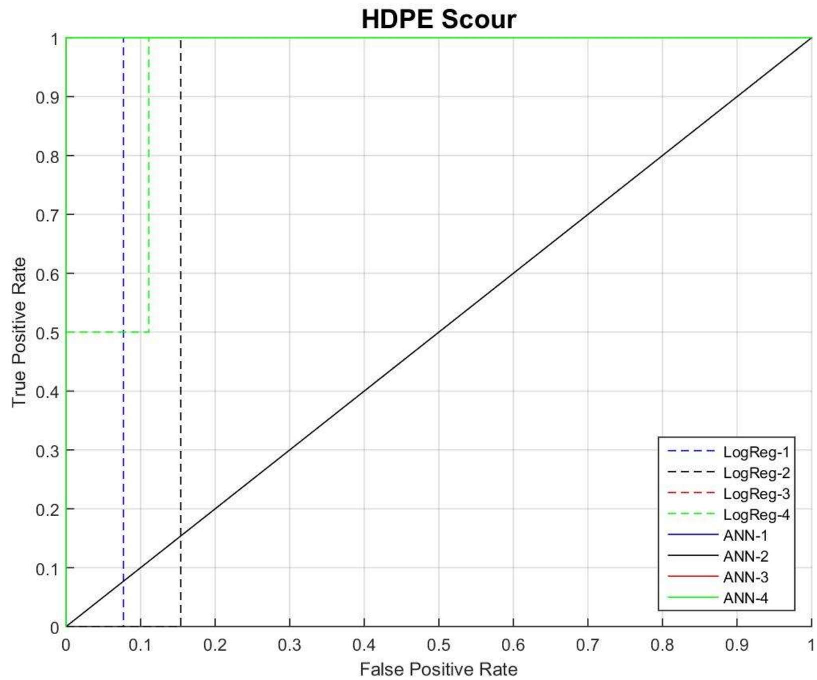


Figure A-35: ROC Curve for HDPE Scour

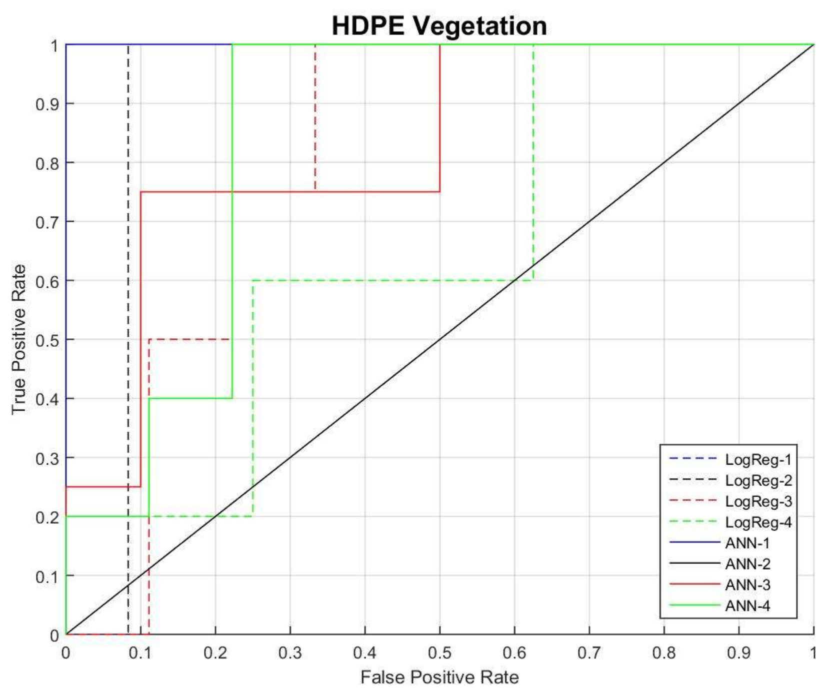


Figure A-36: ROC Curve for HDPE Vegetation

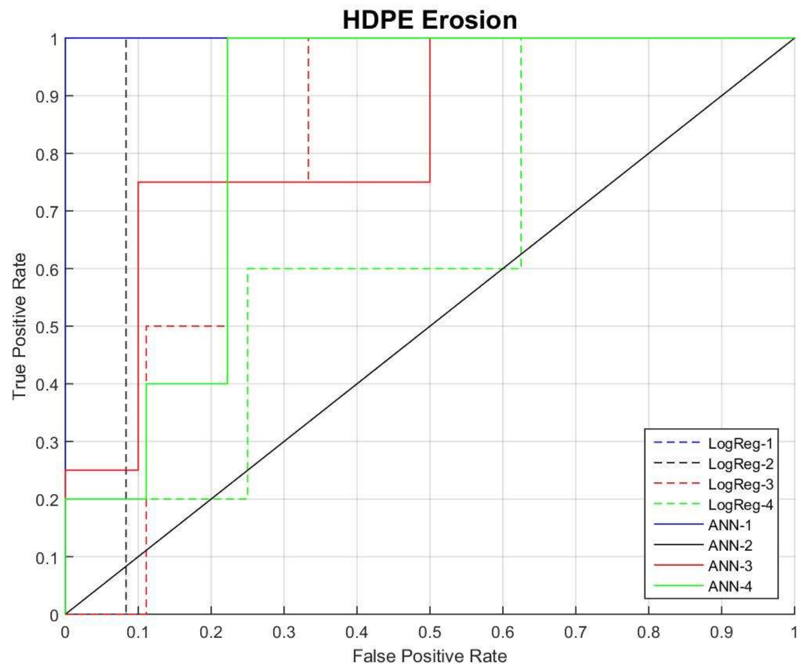


Figure A-37: ROC Curve for HDPE Erosion

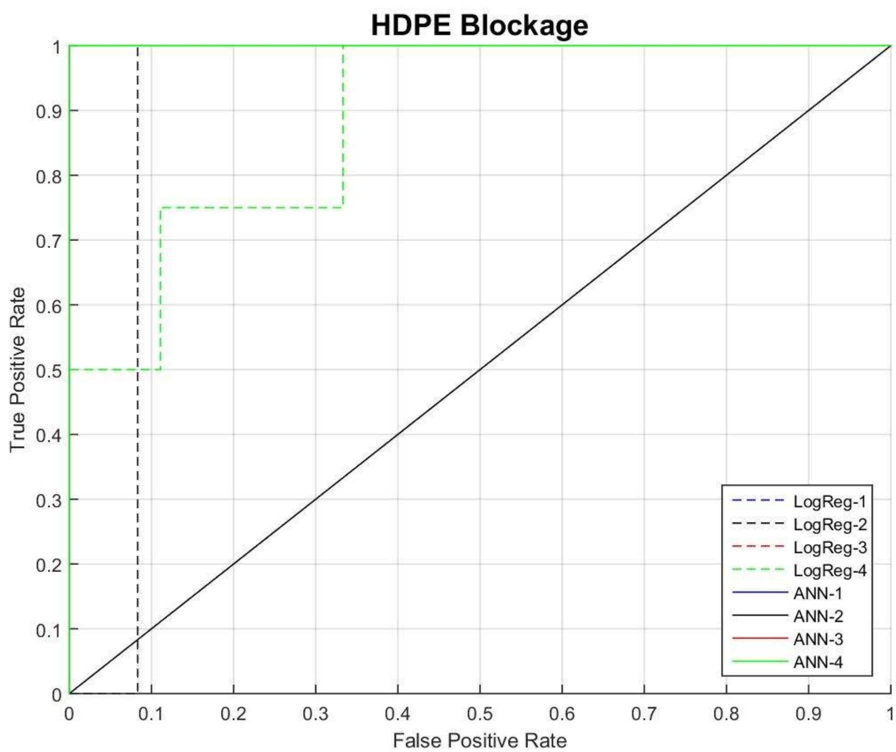


Figure A-38: ROC Curve for HDPE Blockage

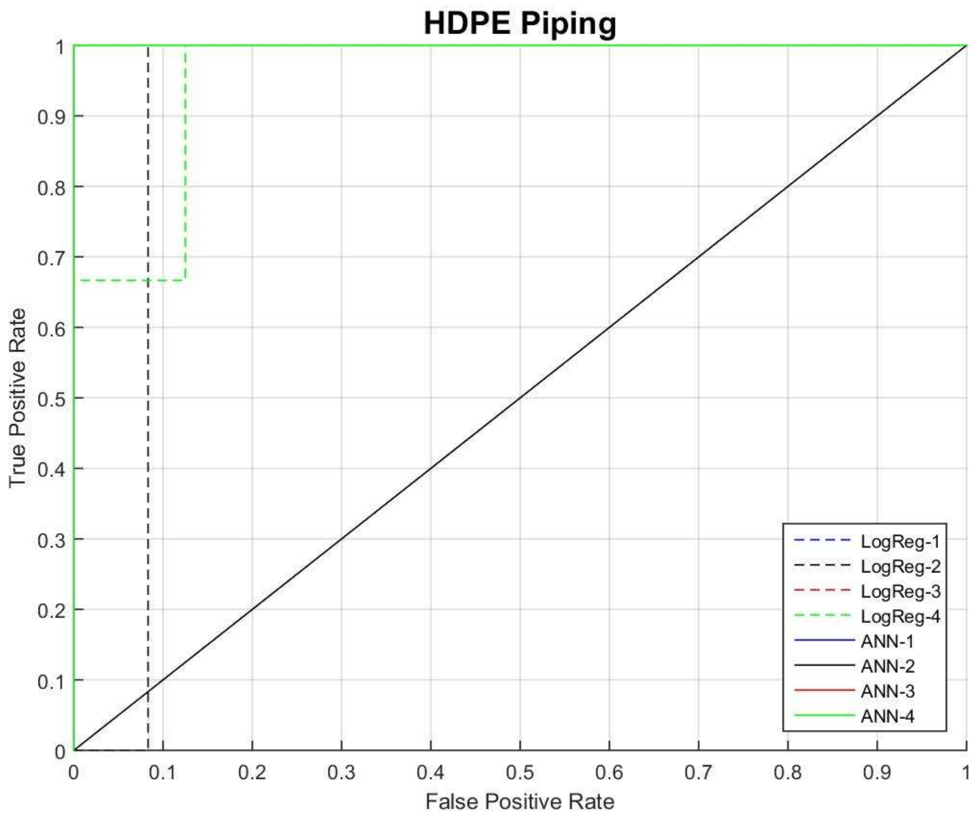


Figure A-39: ROC Curve for HDPE Piping

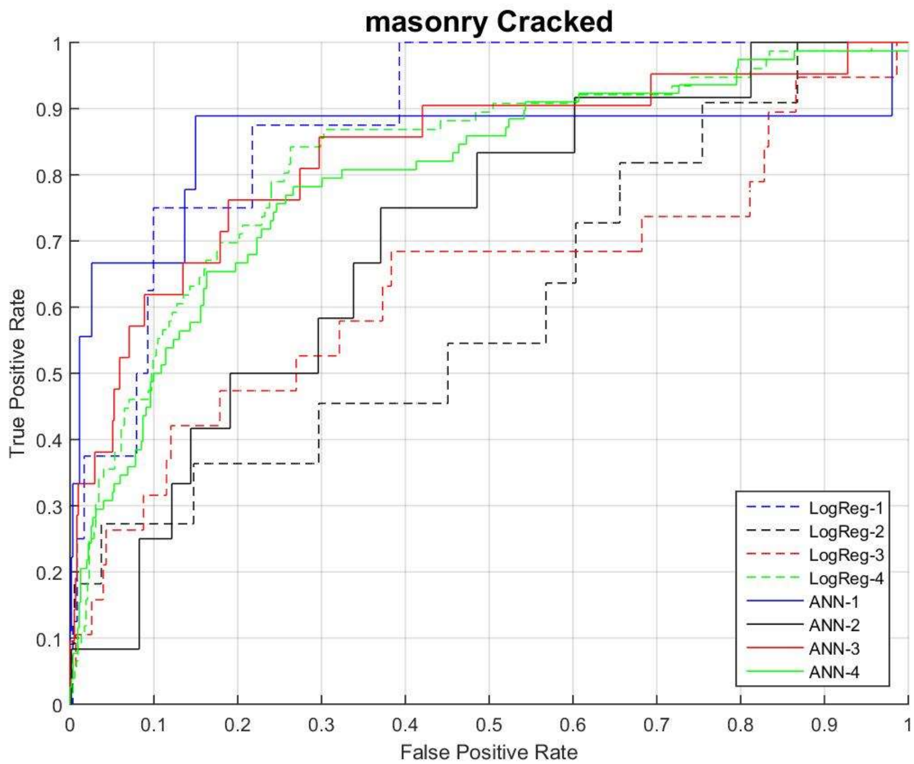


Figure A-40: ROC Curve for Masonry Cracked

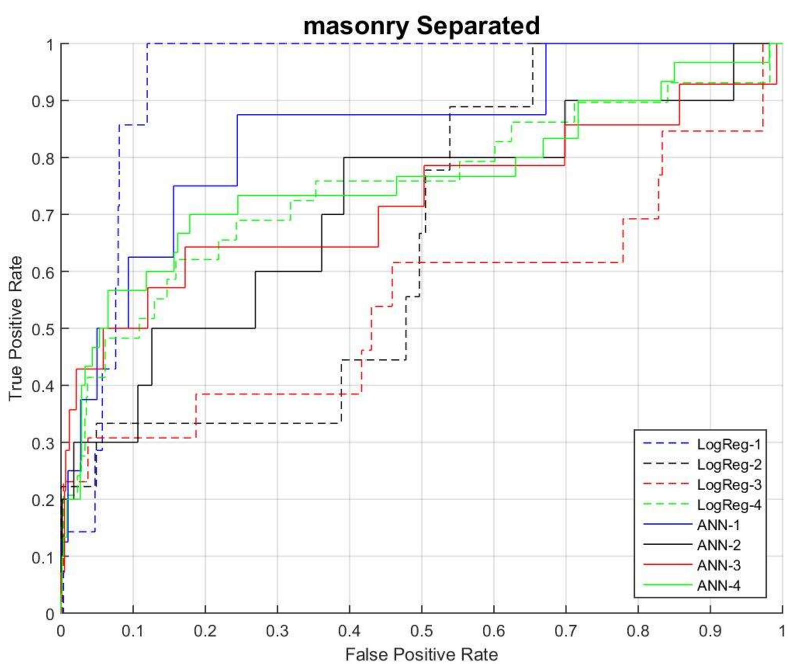


Figure A-41: ROC Curve for Masonry Separated

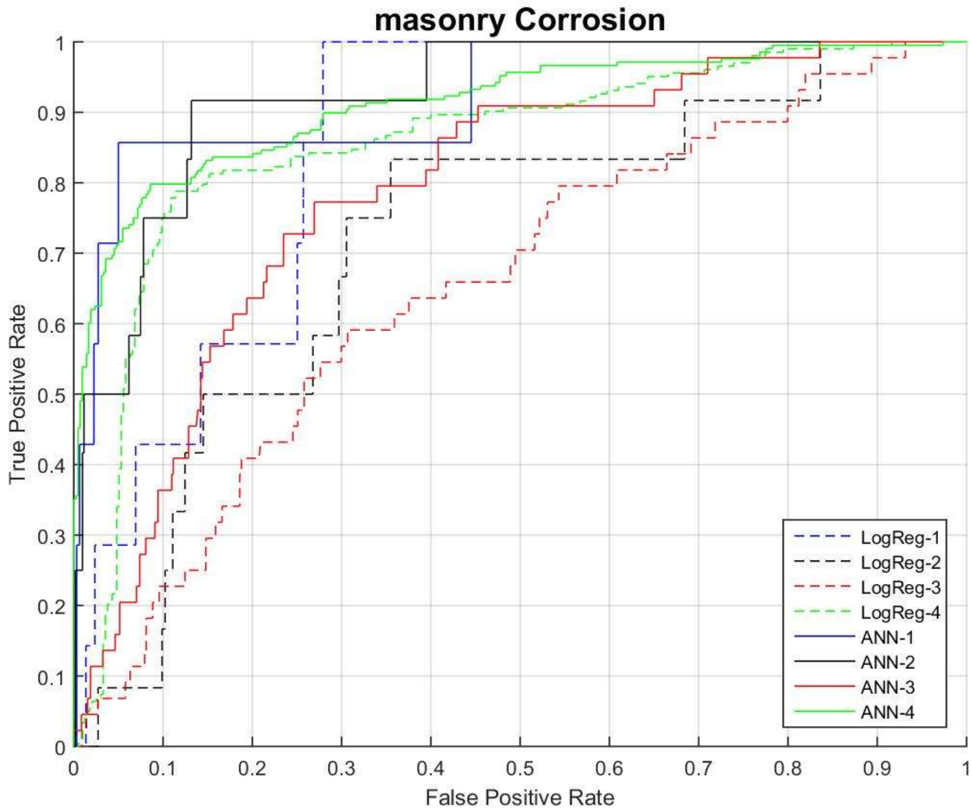


Figure A-42: ROC Curve for Masonry Corrosion

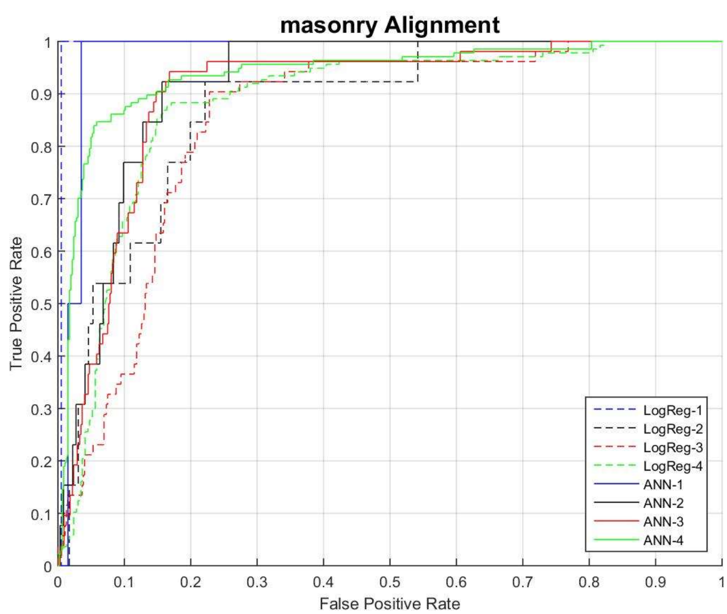


Figure A-43: ROC Curve for Masonry Alignment

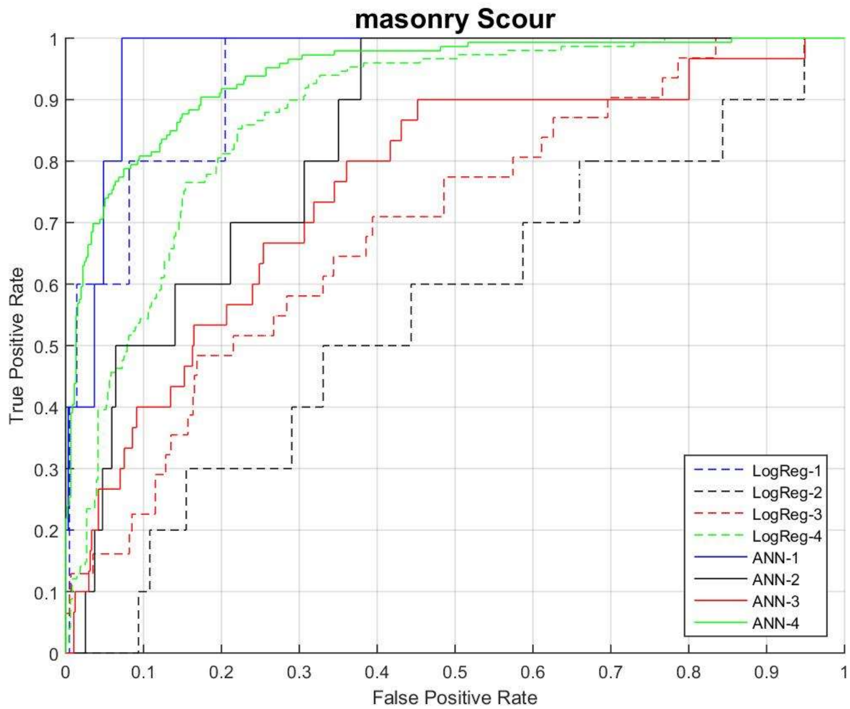


Figure A-44: ROC Curve for Masonry Scour

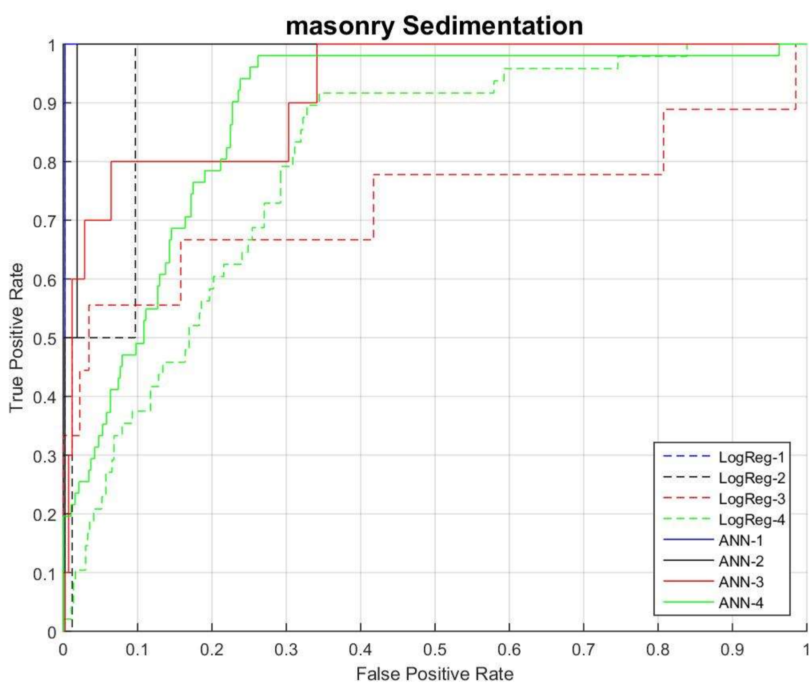


Figure A-45: ROC Curve for Masonry Sedimentation

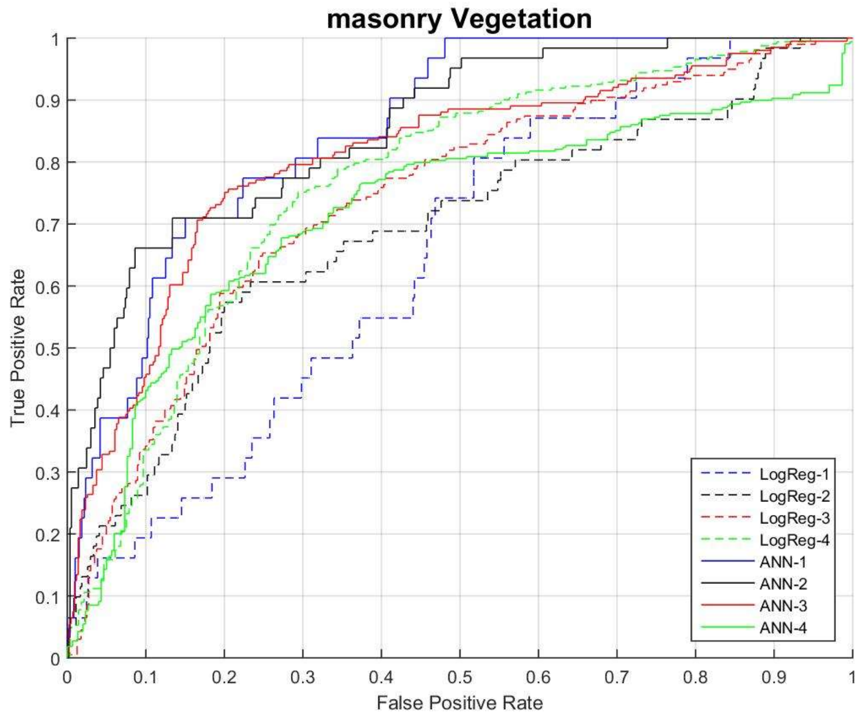


Figure A-46: ROC Curve for Masonry Vegetation

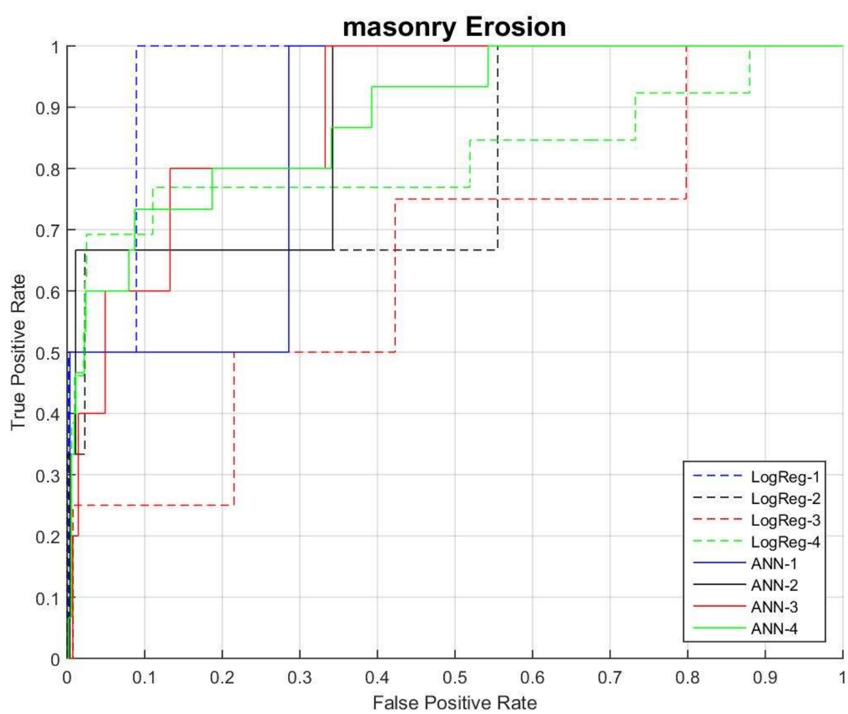


Figure A-47: ROC Curve for Masonry Erosion

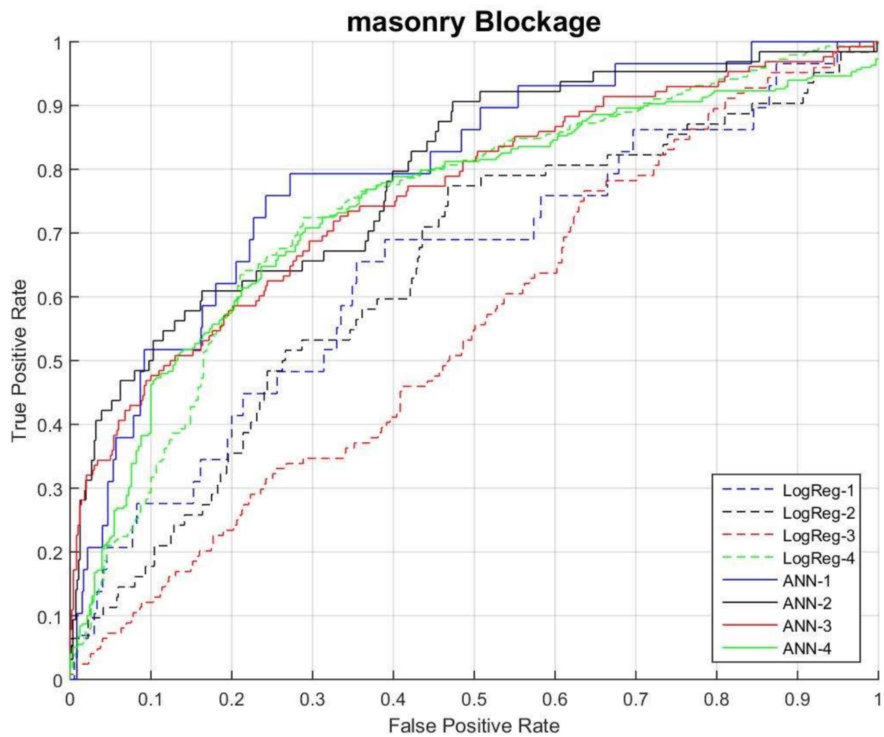


Figure A-48: ROC Curve for Masonry Blockage

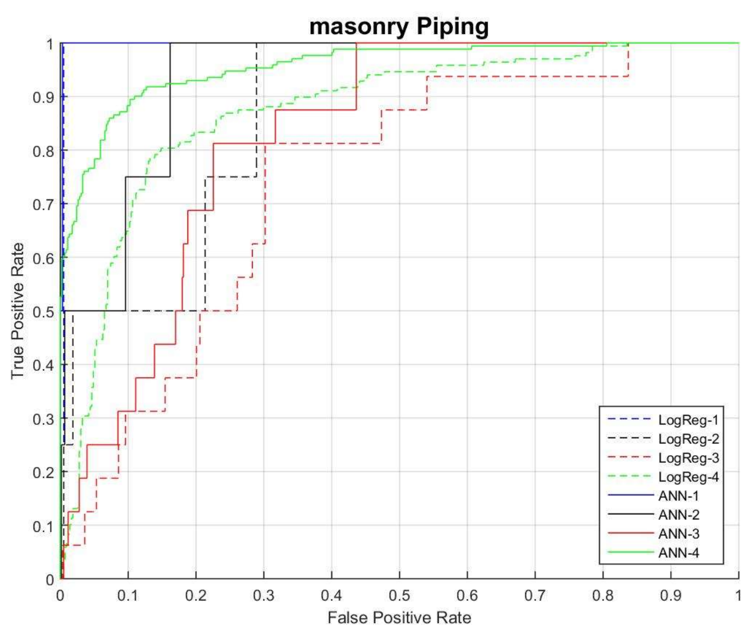


Figure A-49: ROC Curve for Masonry Piping

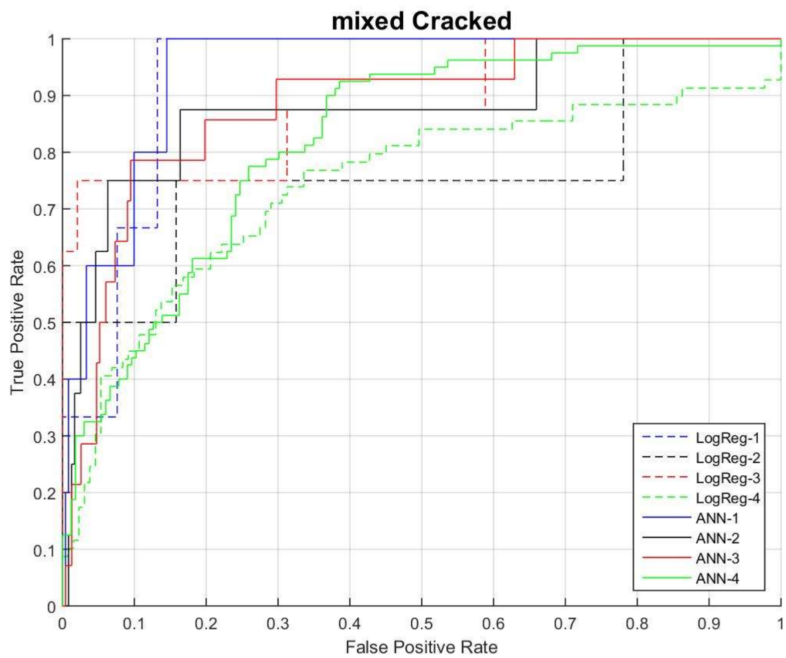


Figure A-50: ROC Curve for Mixed/Other Cracked

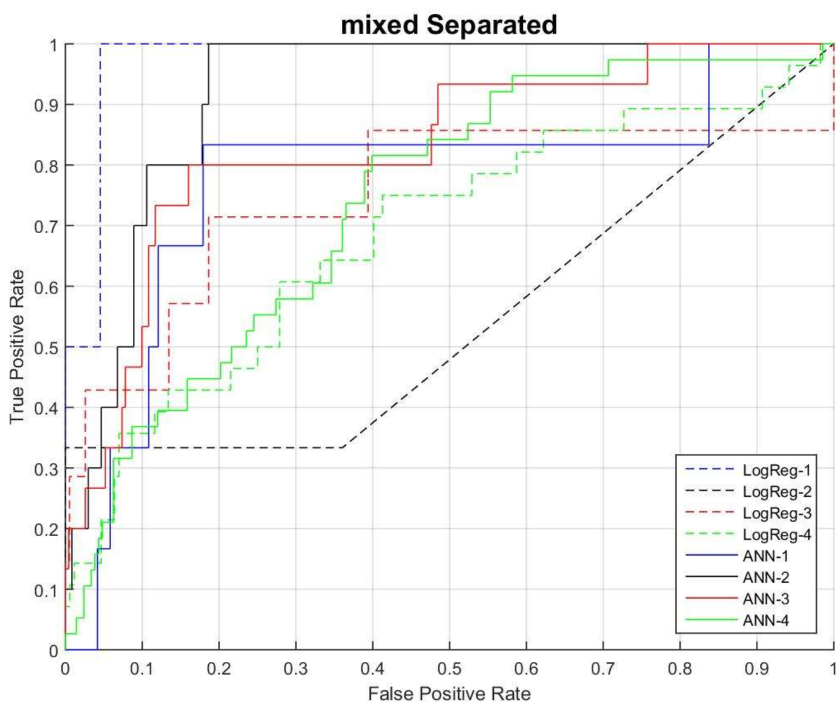


Figure A-51: ROC Curve for Mixed/Other Separated

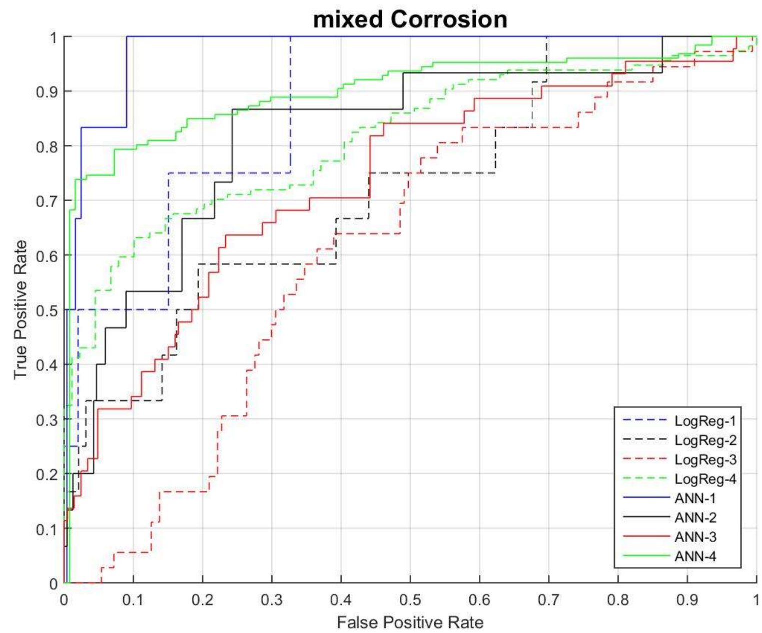


Figure A-52: ROC Curve for Mixed/Other Corrosion

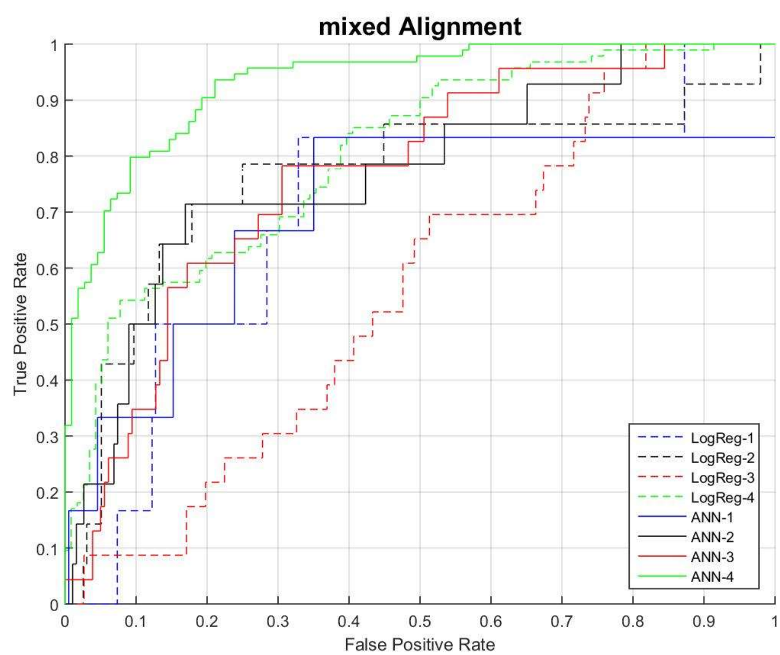


Figure A-53: ROC Curve for Mixed/Other Alignment

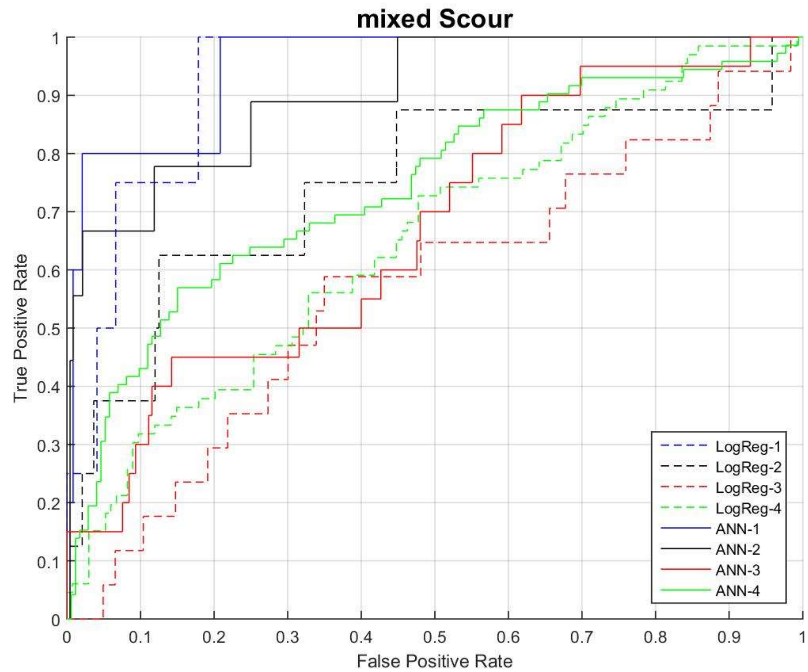


Figure A-54: ROC Curve for Mixed/Other Scour

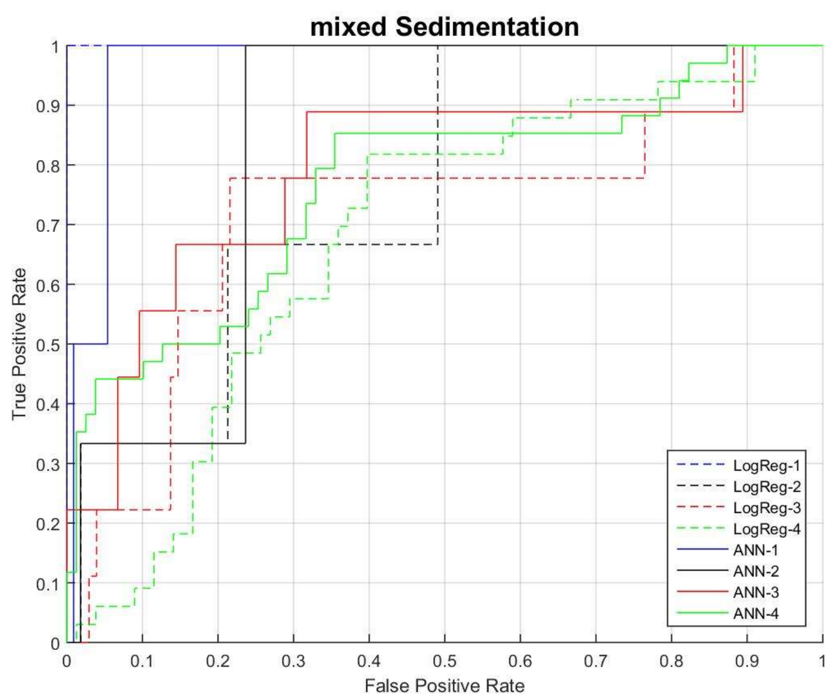


Figure A-55: ROC Curve for Mixed/Other Sedimentation

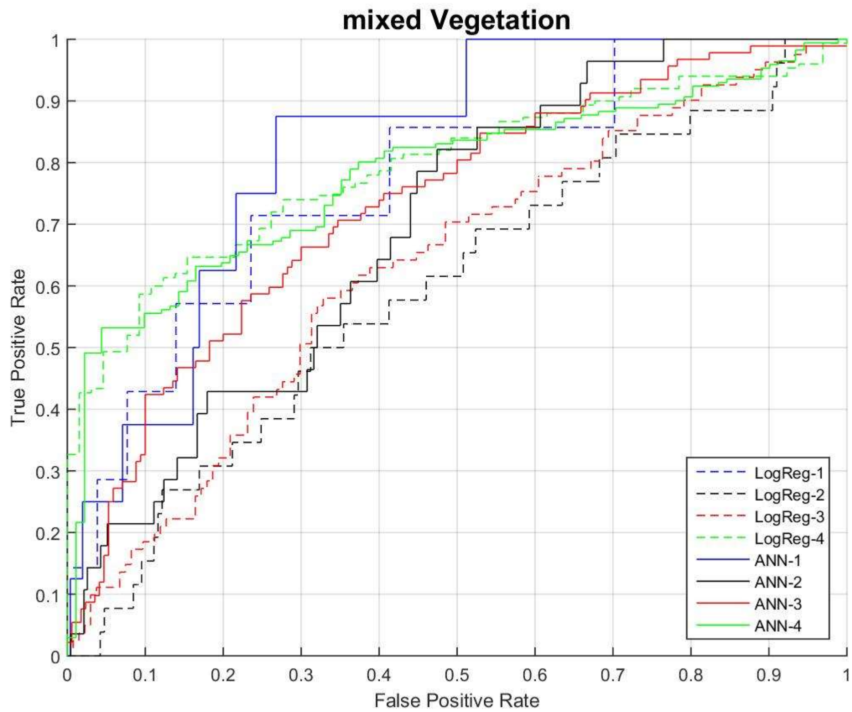


Figure A-56: ROC Curve for Mixed/Other Vegetation

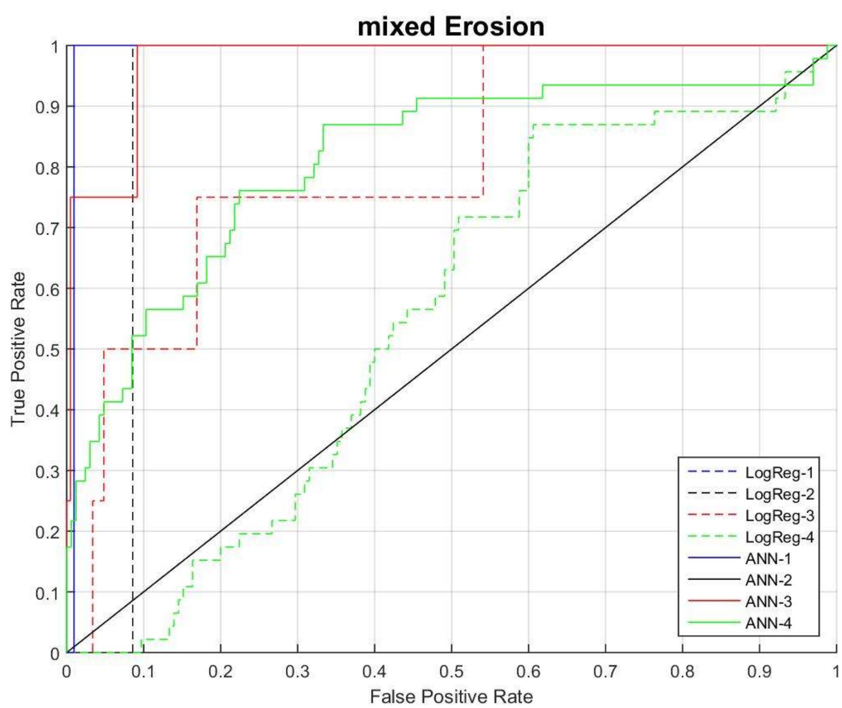


Figure A-57: ROC Curve for Mixed/Other Erosion

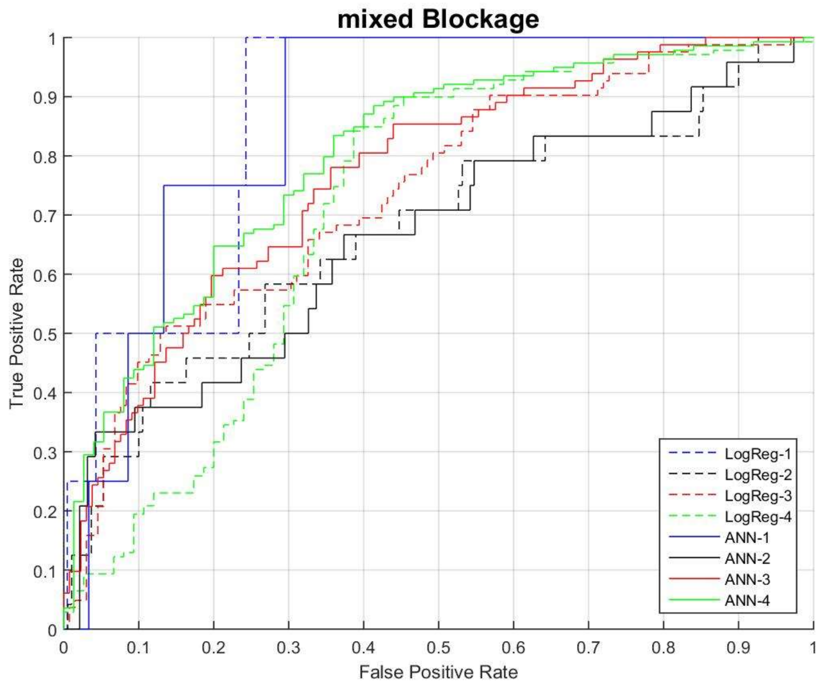


Figure A-58: ROC Curve for Mixed/Other Blockage

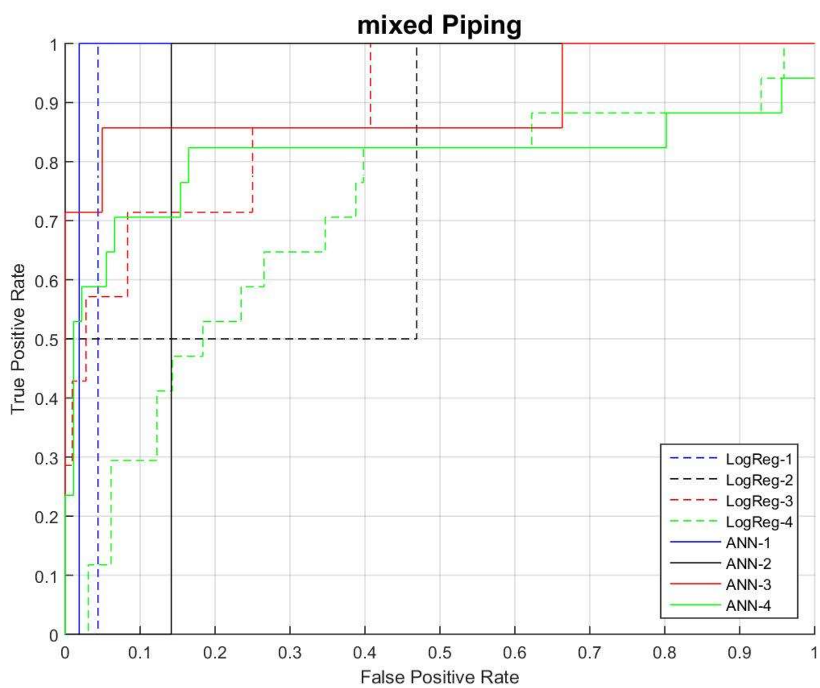


Figure A-59: ROC Curve for Mixed/Other Piping

Appendix B

Figures Using Composite Score to Post-Process the Model

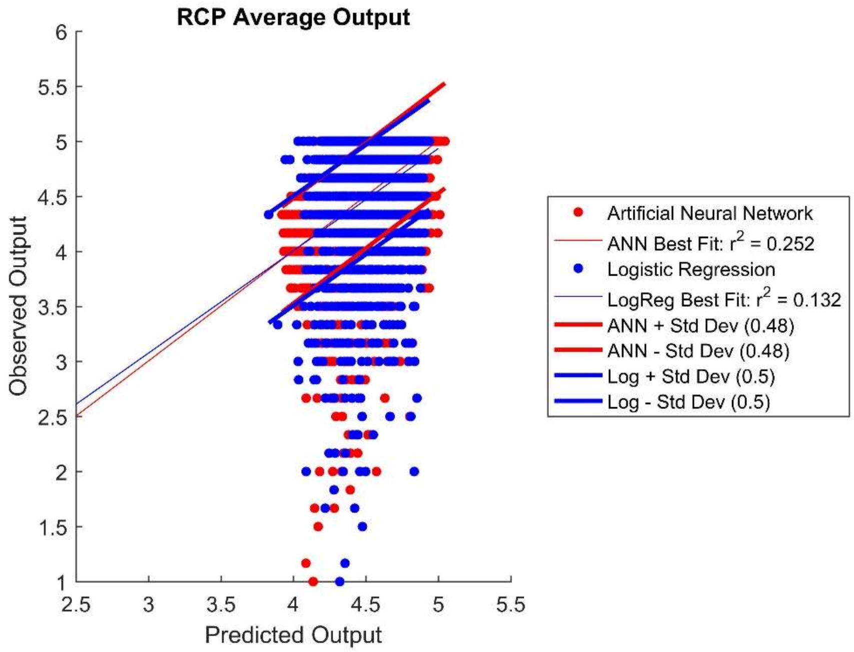


Figure B-1: RCP Average Composite Score

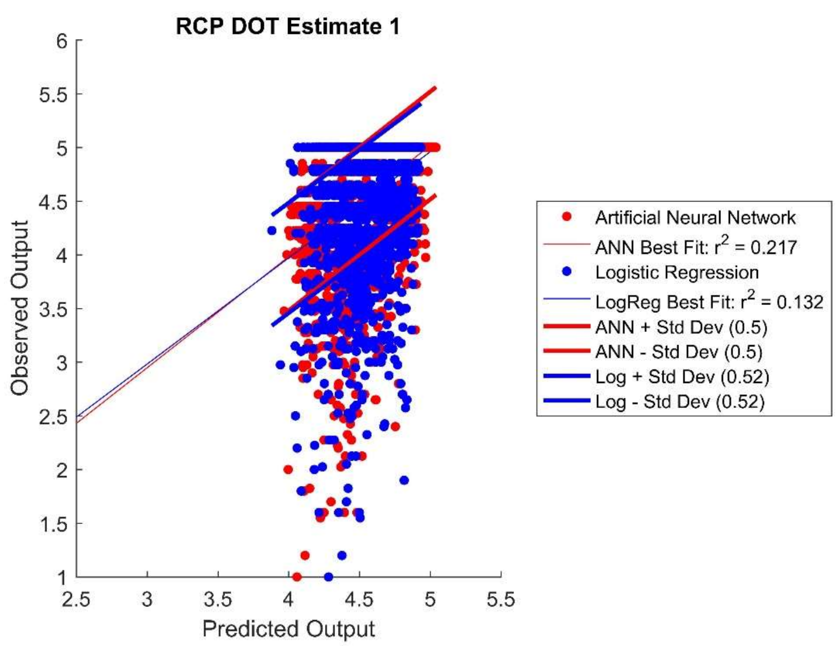


Figure B-2: RCP DOT Estimate 1 Composite Score

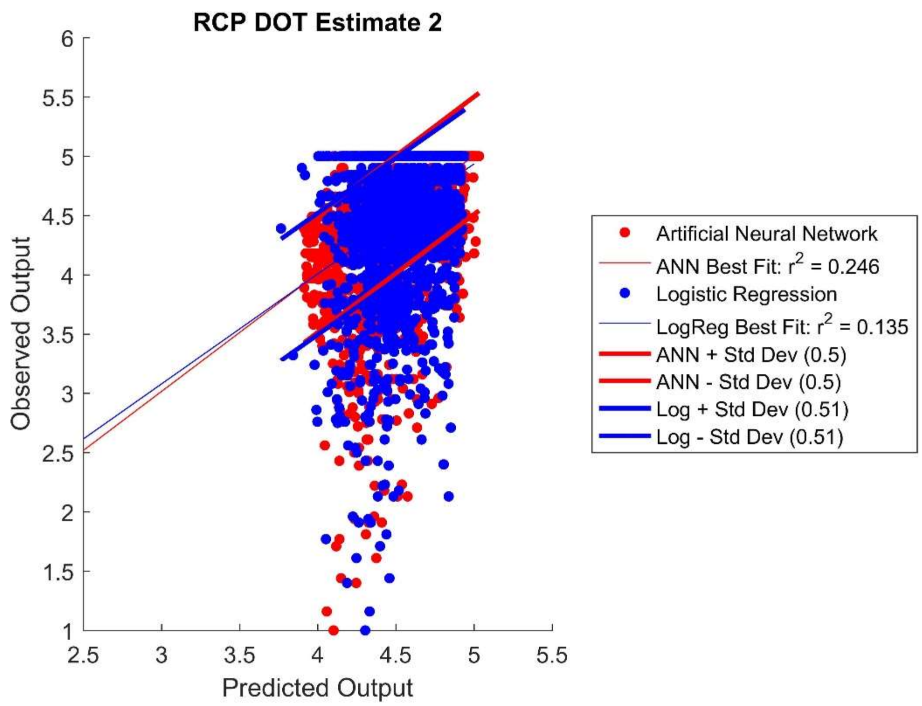


Figure B-3: RCP DOT Estimate 2 Composite Score

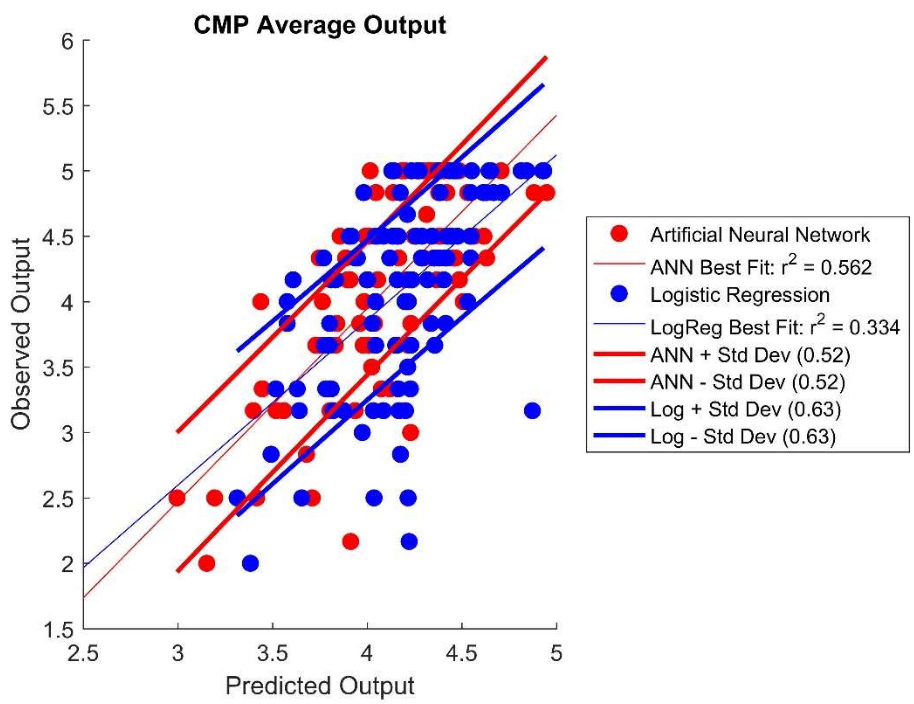


Figure B-4: CMP Average Composite Score

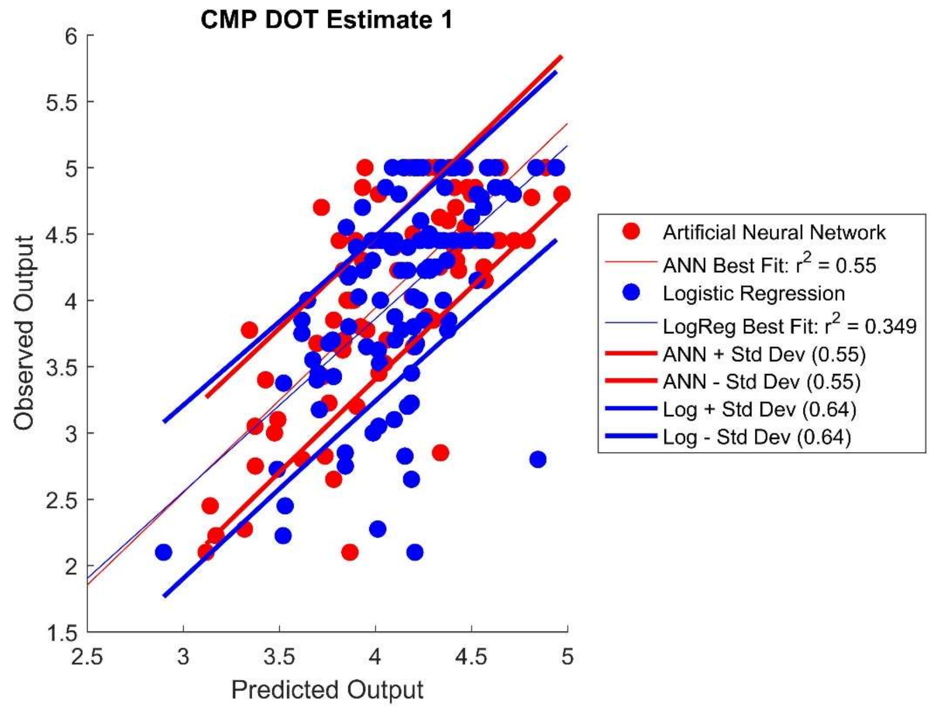


Figure B-5: CMP DOT Estimate 1 Composite Score

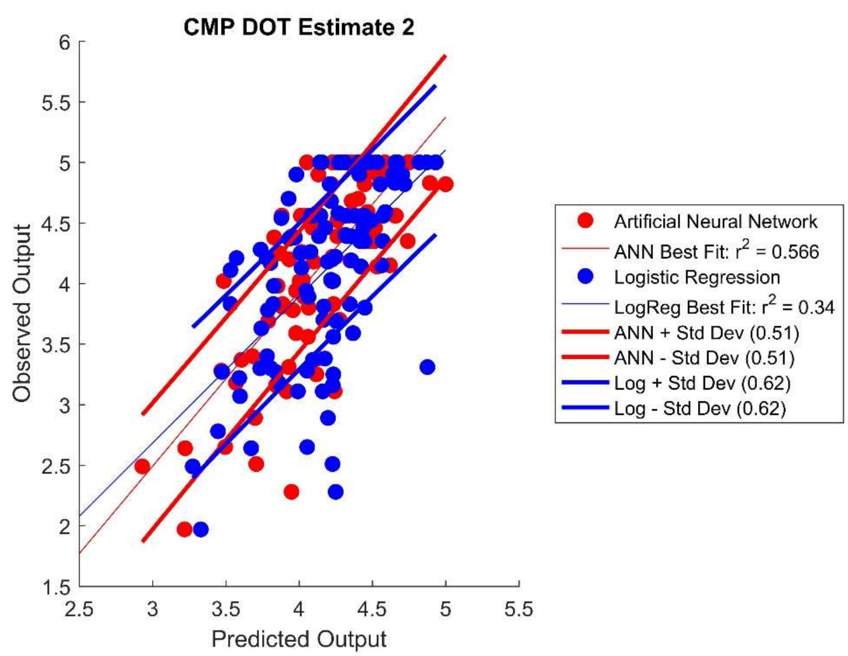


Figure B-6: CMP DOT Estimate 2 Composite Score

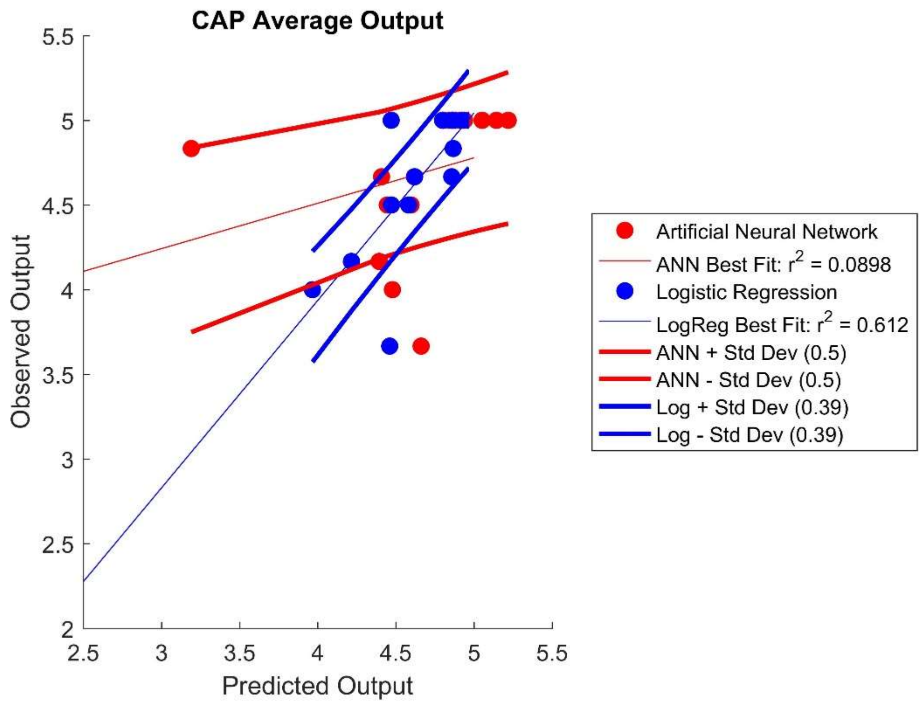


Figure B-7: CAP Average Composite Score

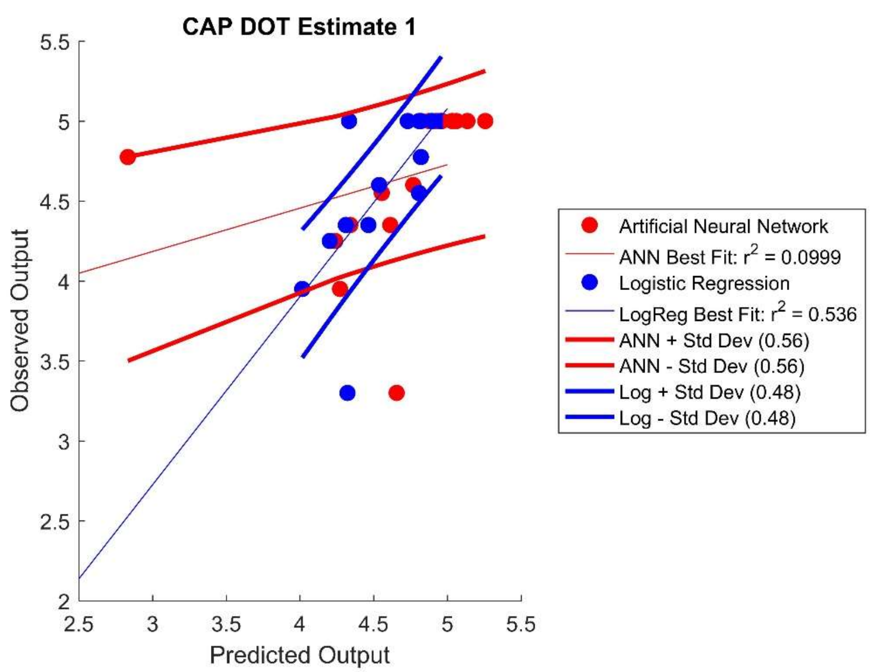


Figure B-8: CAP DOT Estimate 1 Composite Score

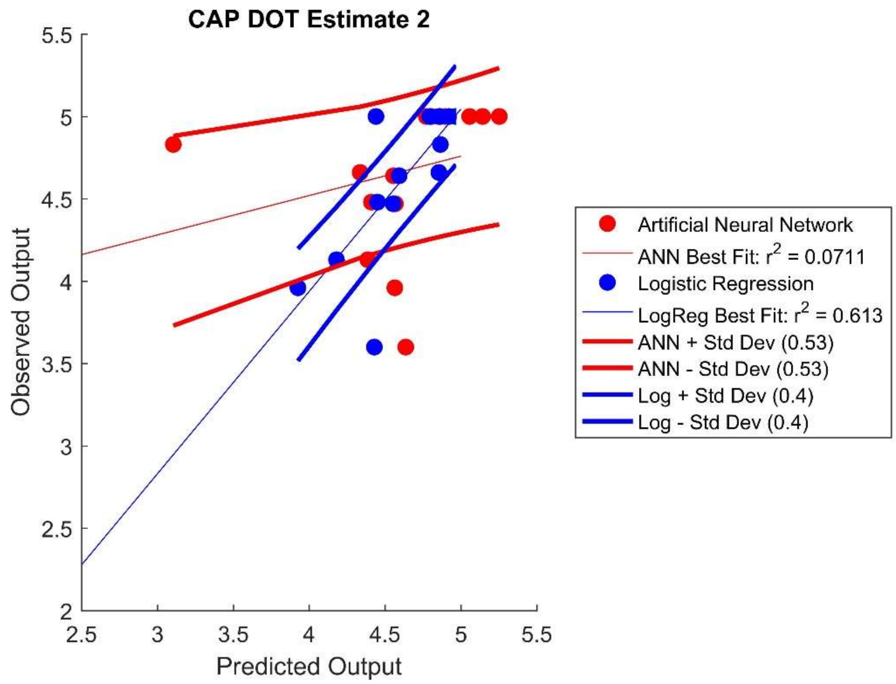


Figure B-9: CAP DOT Estimate 2 Composite Score

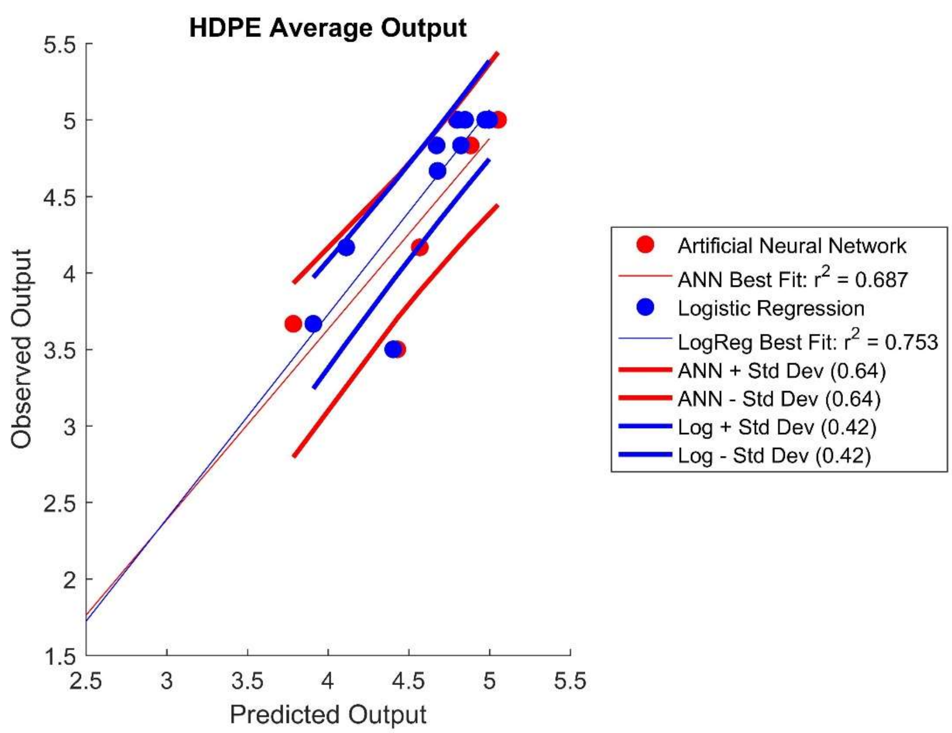


Figure B-10: HDPE Average Composite Score

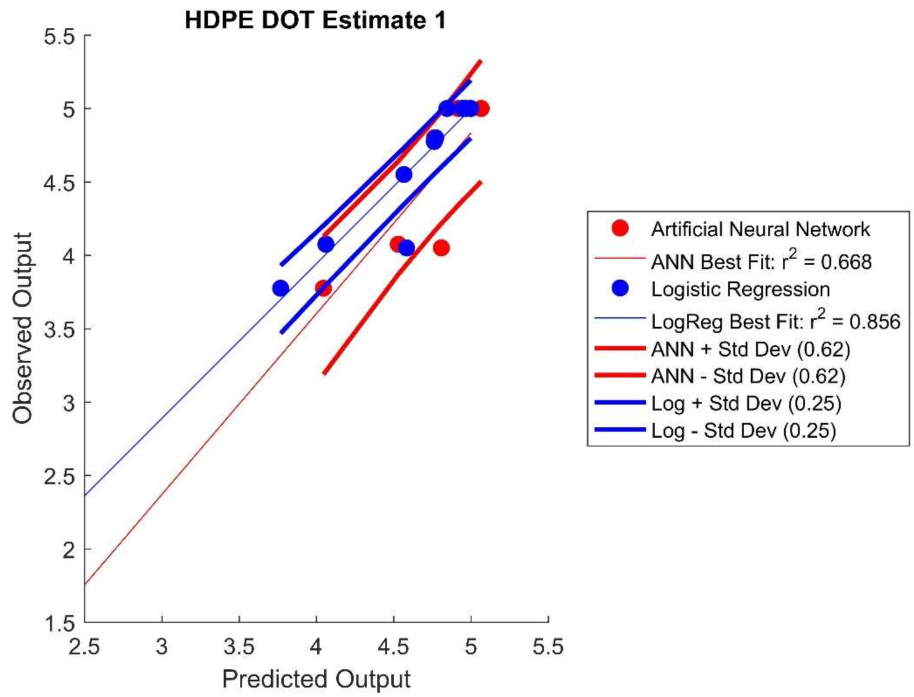


Figure B-11: HDPE DOT Estimate 1 Composite Score

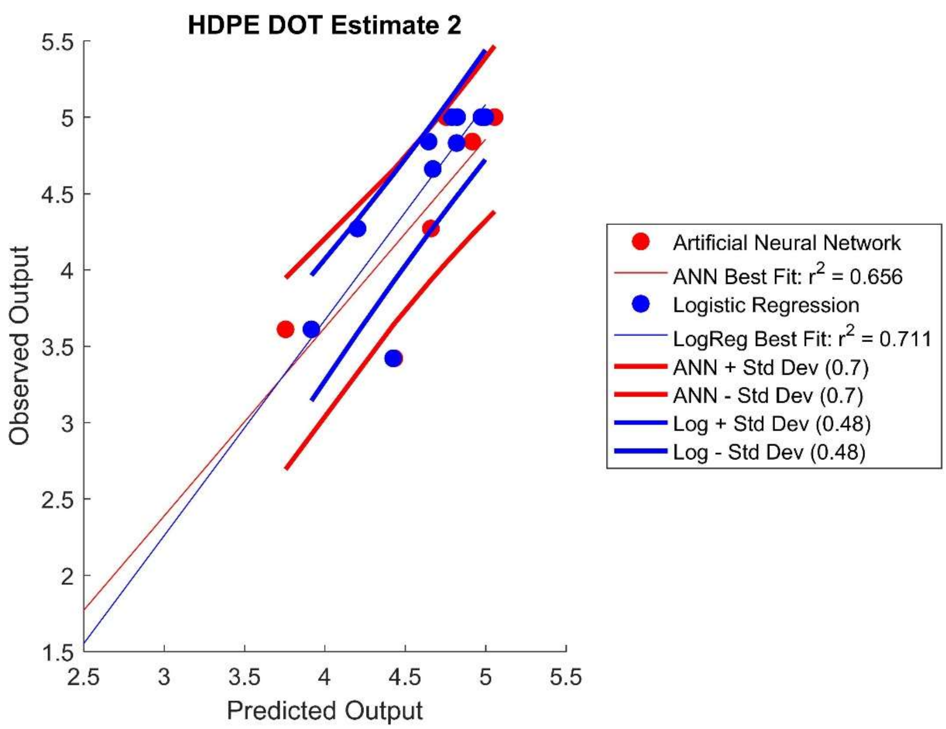


Figure B-12: HDPE DOT Estimate 2 Composite Score

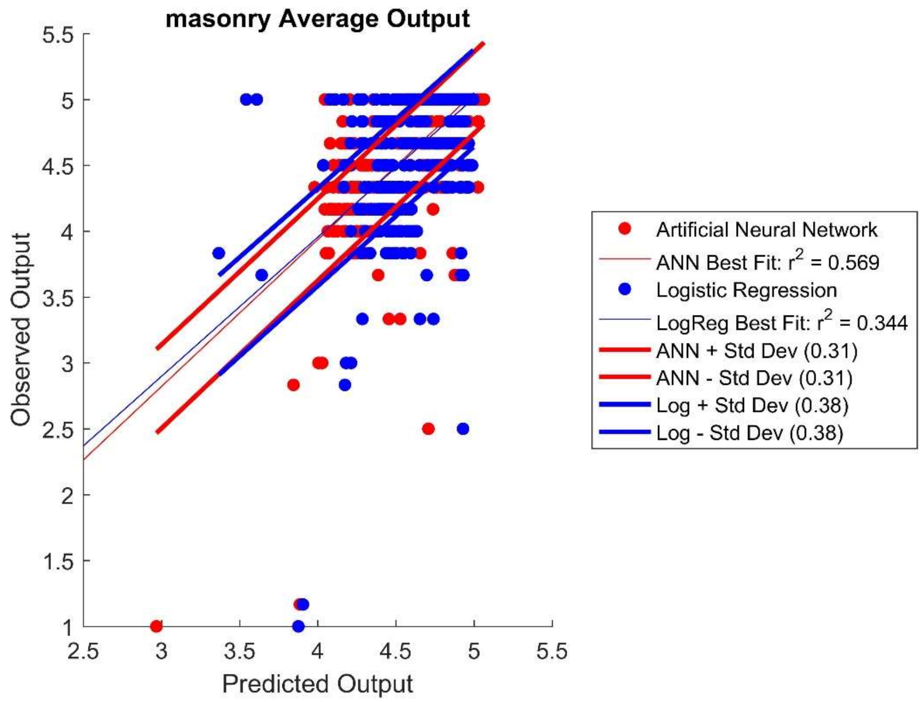


Figure B-13: Masonry Average Composite Score

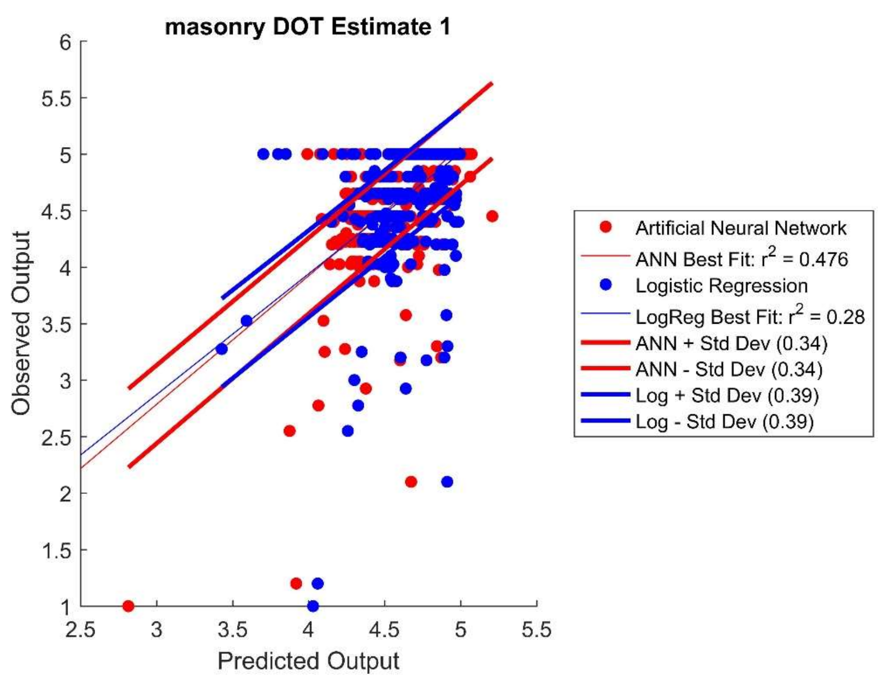


Figure B-14: Masonry DOT Estimate 1 Composite Score

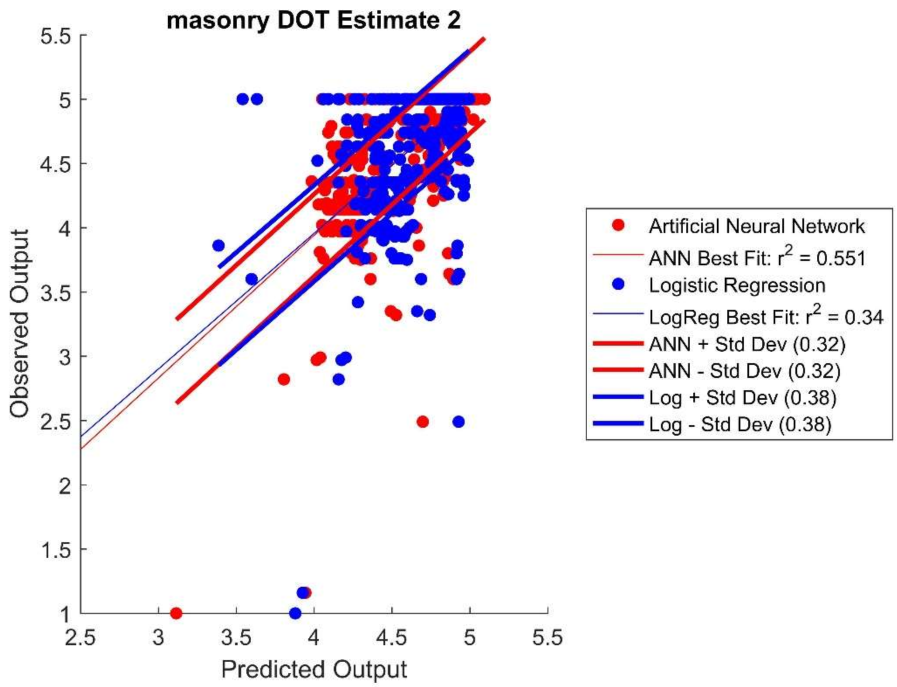


Figure B-15: Masonry DOT Estimate 2 Composite Score

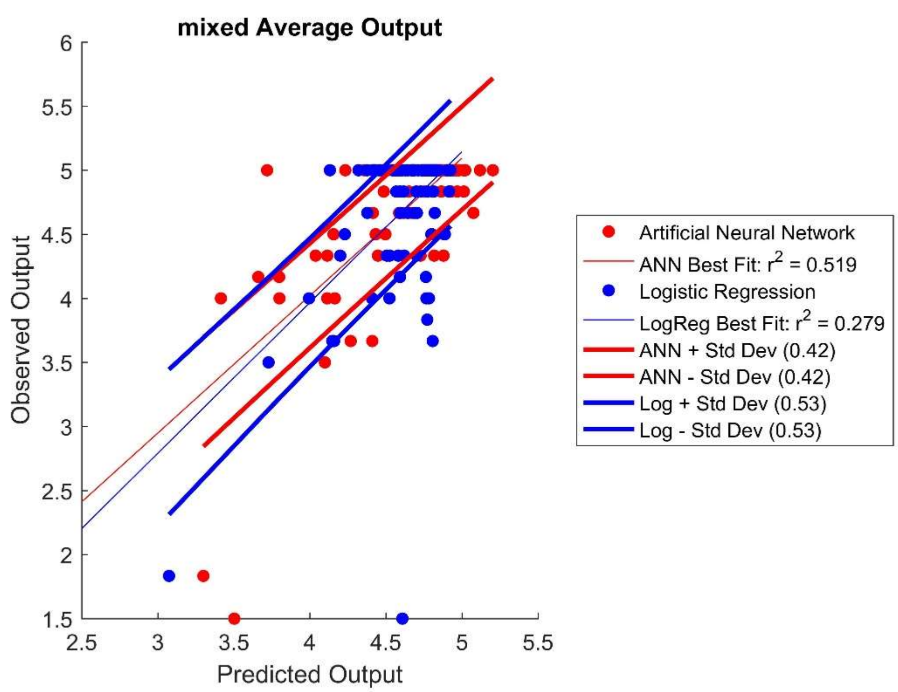


Figure B-16: Mixed Average Composite Score

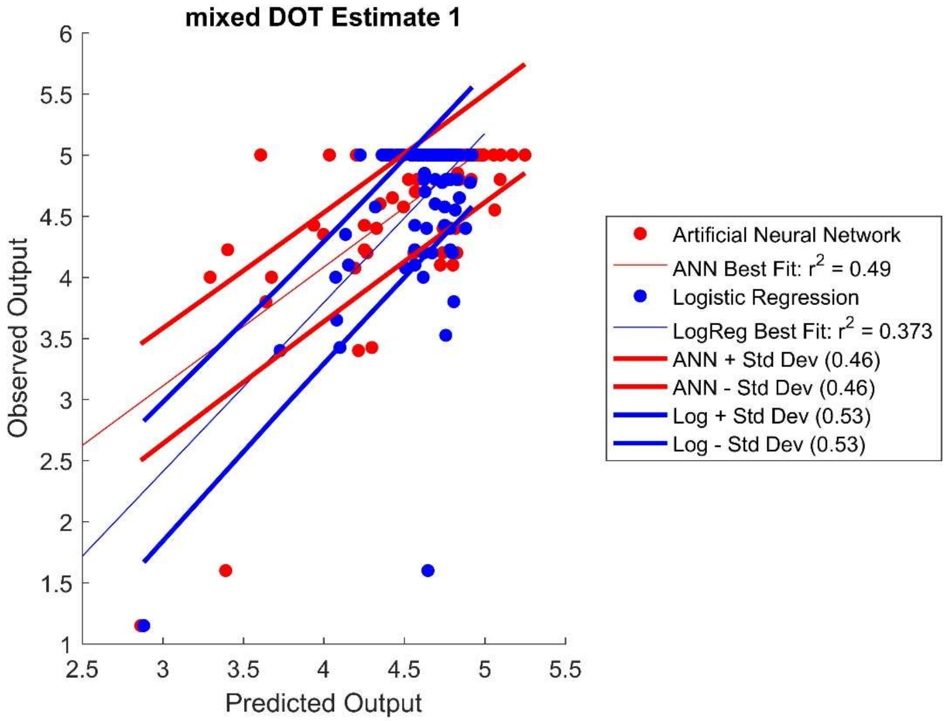


Figure B-17: Mixed DOT Estimate 1 Composite Score

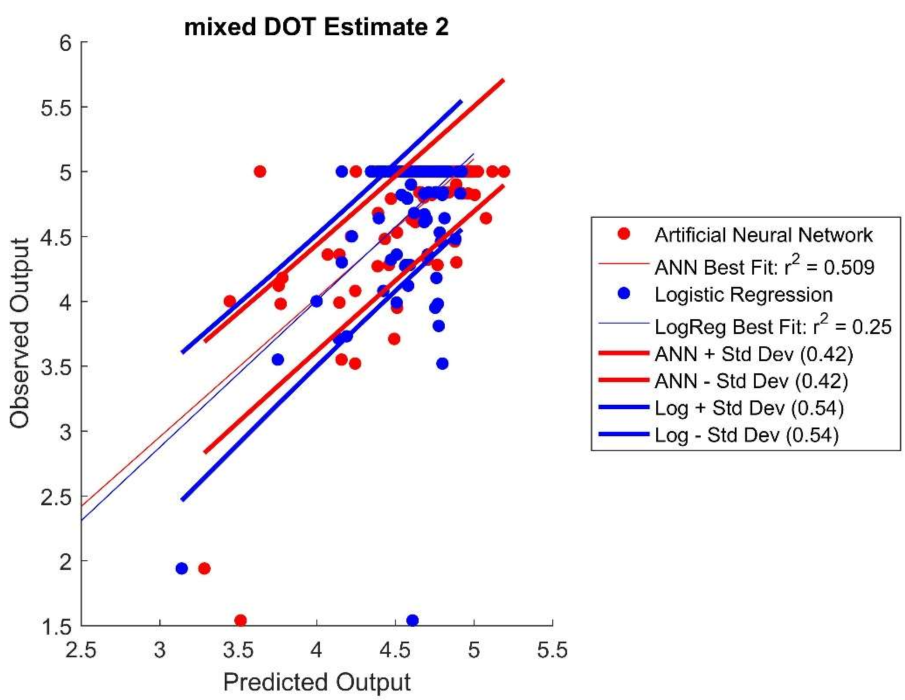


Figure B-18: Mixed DOT Estimate 2 Composite Score

Appendix C

Age Information Analysis

In every culvert prediction model surveyed, culvert age played a significant role in the model. Without this information, or any time-dependent information, the model remains a predictive model and does not change over time. The only factors that would change over time for the proposed model are the annual average temperature, precipitation, and pH values. Even these values are relatively resistant to change as they are the average of the past 30 years of measured data. Given this weakness and constraint in the proposed model, time information was requested for a number of the culverts shown in the SCDOT database. The installation data was determined for a total of 29 corrugated metal pipe (CMP) culverts were provided. The distribution of this data in terms of the amount of culverts in each age category is shown in **Figure C-1**.

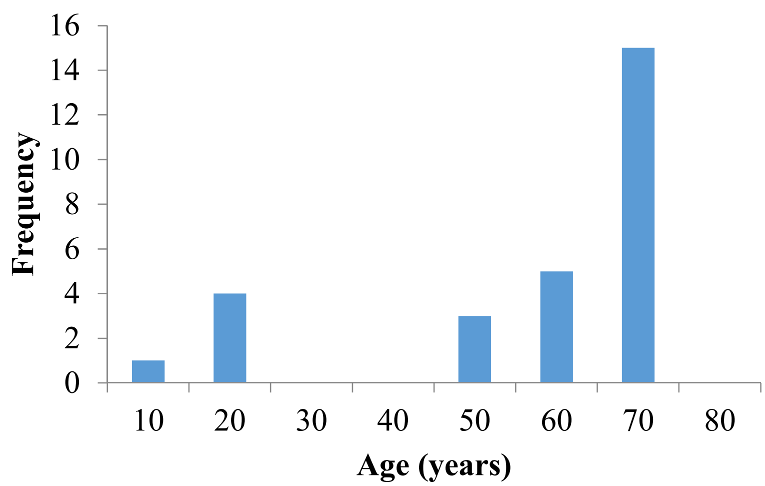


Figure C-1: Distribution of Ages for Specified Culverts

The distribution of age information is not ideal as over half of the given information shows culverts over 60 years old. If this distribution proved to be representative of the distribution of culvert ages across the state of South Carolina, then the data could be used to create models for CMP culverts. **Table C-1** shows the distribution of ratings for the culverts for which the installation date was given. This distribution follows relatively the same distribution as the overall culvert database meaning the data could produce results applicable to all CMP culverts.

Table C-1: Distribution of Culvert Ratings Compared to Overall Database

Rating	Total	Percent	Percent of Total Database
5	386	58.9%	69.84%
4	170	26.0%	18.74%
3	71	10.8%	6.93%
2	21	3.2%	2.32%
1	7	1.1%	2.17%

The same procedure used to create a logistic regression and artificial neural network using the entire database was applied to the 29 data points with age information. The results of this procedure were compared to those of the procedure without age information (**Table C-2**). These results showed that two of the ten output variables were better explained with age as an additional input (scour and piping) in both the logistic regression and neural network models. The neural network model addressing cracking was also improved by adding the installation date as an input.

Table C-2: Comparison of AUC for Models with and without Age

		COMBINATION NUMBER													
		1	10	11	12	13	2	3	4	5	6	7	8	9	Max Area
CMP - Logistic Regression	**Cracked**	2.615	2.431	2.412	2.523	2.977	2.472	2.399	2.600	2.582	2.940	2.683	2.674	0.000	13
	Separated	2.873	2.716	2.755	2.850	2.955	2.784	2.646	2.745	2.732	3.202	2.935	2.840	0.000	6
	Corrosion	2.798	2.560	2.488	2.808	3.147	2.577	2.765	2.751	2.606	3.157	2.806	2.866	0.000	6
	Alignment	3.295	2.899	2.859	3.080	3.226	2.931	3.054	3.265	3.258	3.171	3.299	3.328	0.000	8
	Scour	3.136	2.449	2.491	2.706	2.807	2.476	2.829	3.106	3.161	2.911	3.162	3.118	0.000	7
	Sedimentation	2.731	2.594	2.689	2.708	2.174	2.552	2.631	2.444	2.684	2.687	2.731	0.000	0.000	1
	Vegetation	3.283	2.966	2.915	3.013	3.029	2.959	3.244	3.293	3.298	3.114	3.311	3.183	0.000	7
	Erosion	3.320	2.950	2.980	2.266	2.633	3.033	3.180	3.316	3.183	2.583	3.324	3.296	0.000	7
	Blockage	2.818	2.455	2.460	2.443	2.667	2.456	2.506	2.777	2.594	2.745	2.803	2.661	0.000	1
	Piping	2.776	2.247	2.371	2.627	2.950	2.241	2.581	2.775	2.788	2.898	2.801	2.839	0.000	13
CMP - Neural Network	**Cracked**	3.117	3.077	3.095	3.119	3.130	3.048	2.884	3.156	3.070	3.286	3.068	3.061	3.118	6
	Separated	3.126	3.125	3.174	3.368	3.307	3.284	3.238	3.059	3.205	3.651	2.965	3.290	3.307	6
	Corrosion	3.307	3.138	3.268	3.040	3.213	3.181	2.948	3.421	3.105	3.234	3.219	3.299	3.168	4
	Alignment	3.259	3.139	3.118	3.186	3.127	3.279	3.206	3.332	3.304	3.266	3.309	3.420	3.462	9
	Scour	3.272	3.225	2.783	2.750	2.890	3.004	3.146	3.121	3.110	3.130	3.189	3.234	3.214	1
	Sedimentation	2.863	2.789	2.894	2.830	2.496	2.678	2.772	2.552	2.800	2.544	2.762	2.592	2.822	11
	Vegetation	3.280	3.344	3.185	2.911	3.458	3.000	3.176	3.330	3.103	3.218	3.304	3.422	3.199	13
	Erosion	3.441	3.454	3.377	2.376	2.477	3.267	3.423	3.450	3.245	2.472	3.503	3.307	3.364	7
	Blockage	2.980	2.762	2.749	2.620	3.071	2.724	2.678	3.014	2.723	2.988	3.000	2.837	3.084	9
	Piping	3.179	3.012	3.141	3.208	3.161	3.108	3.037	2.953	3.061	3.140	3.030	3.142	3.083	12
CMP-AGE Logistic Regression	**Cracked**	1.962	2.886	2.911	2.536	2.078	1.975	2.927	2.541	2.689	2.890	2.078	2.098	2.001	3
	Separated	2.122	2.140	2.242	2.170	2.225	2.109	2.246	2.098	2.184	2.091	2.225	2.345	2.495	9
	Corrosion	2.735	2.582	2.156	1.255	2.217	2.730	2.502	2.789	2.426	2.365	2.217	2.330	1.206	4
	Alignment	1.705	1.747	1.786	1.289	1.297	1.712	1.649	1.309	1.303	1.211	1.297	1.227	1.434	11
	Scour	3.296	3.359	2.961	2.663	2.633	3.288	2.989	3.122	3.157	3.285	2.633	2.846	1.619	10
	Sedimentation	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1
	Vegetation	1.329	1.510	1.542	1.719	1.371	1.303	1.535	1.392	1.586	1.756	1.371	1.374	1.556	6
	Erosion	2.407	2.413	1.176	2.122	1.606	2.437	2.333	1.641	2.631	2.200	1.606	1.606	2.188	5
	Blockage	1.441	1.542	1.503	1.371	1.547	1.467	1.637	1.584	1.673	1.369	1.547	1.490	1.472	5
	Piping	2.229	1.867	2.078	2.906	2.110	1.649	3.142	2.969	2.207	2.876	2.110	1.964	2.984	3
CMP-AGE Neural Network	**Cracked**	3.131	3.279	3.064	3.132	3.088	3.153	3.223	3.151	3.286	3.092	3.088	2.950	3.345	9
	Separated	3.200	3.223	3.144	3.075	3.241	3.229	3.016	3.227	3.084	3.105	3.241	3.099	3.112	13
	Corrosion	2.693	2.862	2.719	2.613	2.685	2.841	2.578	2.795	2.728	2.750	2.685	2.618	2.581	10
	Alignment	1.771	1.906	1.772	1.761	1.769	1.793	1.754	1.791	1.750	1.798	1.769	1.875	1.759	10
	Scour	3.389	3.254	3.317	3.095	3.411	3.183	3.267	3.578	3.214	3.385	3.411	3.300	3.416	4
	Sedimentation	1.500	1.500	1.500	1.500	1.500	1.500	1.500	1.500	1.500	1.500	1.500	1.500	1.500	1
	Vegetation	1.691	1.501	1.630	1.786	1.790	1.695	1.746	1.644	1.856	1.722	1.790	1.875	1.833	8
	Erosion	2.553	2.586	2.676	2.363	2.789	2.403	2.667	2.716	2.439	2.617	2.789	2.787	2.776	13
	Blockage	1.692	1.725	1.780	1.662	1.840	1.784	1.694	1.855	1.781	1.789	1.840	1.856	1.767	8
	Piping	3.556	3.514	3.428	3.646	3.492	3.558	3.134	3.679	3.563	3.554	3.492	3.573	3.305	4

A comparison of the best models reveals that the change in the model in terms of area under the ROC curve shows an increase of less than 7% in the cases where logistic regression models were improved. The neural network was slightly more improved with close to 15% improvement in the piping model and nearly 10% improvement in the scour model. The full breakdown of the comparison between the best models with and without age as an input is shown in **Table C-3**.

Table C-3: Comparison of Change of Models with Age Information

	Best AUC					
	LogReg	**LogReg-Age**	**% Change**	**ANN**	**ANN-Age**	**% Change**
Cracked	2.977	2.911	-2.2%	3.286	3.345	1.8%
Separated	3.202	2.495	-22.1%	3.651	3.241	-11.2%
Corrosion	3.157	2.789	-11.7%	3.421	2.862	-16.4%
Alignment	3.328	1.786	-46.3%	3.462	1.906	-44.9%
Scour	3.162	3.359	6.2%	3.272	3.578	9.4%
Sedimentation	2.731	1.000	-63.4%	2.894	1.500	-48.2%
Vegetation	3.311	1.756	-47.0%	3.458	1.875	-45.8%
Erosion	3.324	2.631	-20.9%	3.503	2.789	-20.4%
Blockage	2.818	1.673	-40.6%	3.084	1.856	-39.8%
Piping	2.950	3.142	6.5%	3.208	3.679	14.7%

To follow the pattern of the calculations of the previous models, the best models were taken and a composite score was calculating using the two detailed DOT methods and the overall average method (**Figure C-2, C-3, and C-4**). Using these methods, the neural network models showed a significant increase in the coefficient of determination (**Table C-4**).

Table C-4: Coefficient of Determination (R^2)

	ANN	ANN-Age	% Change	LogReg	LogReg-Age	% Change
DOT Est 1	0.562	0.772	37.2%	0.334	0.627	88.0%
DOT Est 2	0.550	0.728	32.4%	0.349	0.628	79.8%
Average	0.566	0.767	35.4%	0.340	0.628	85.0%

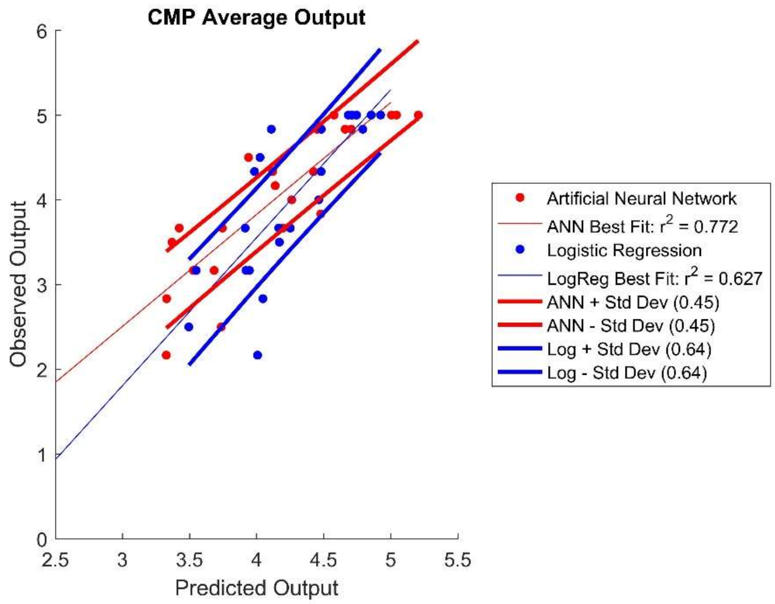


Figure C-2: CMP Average Composite Score

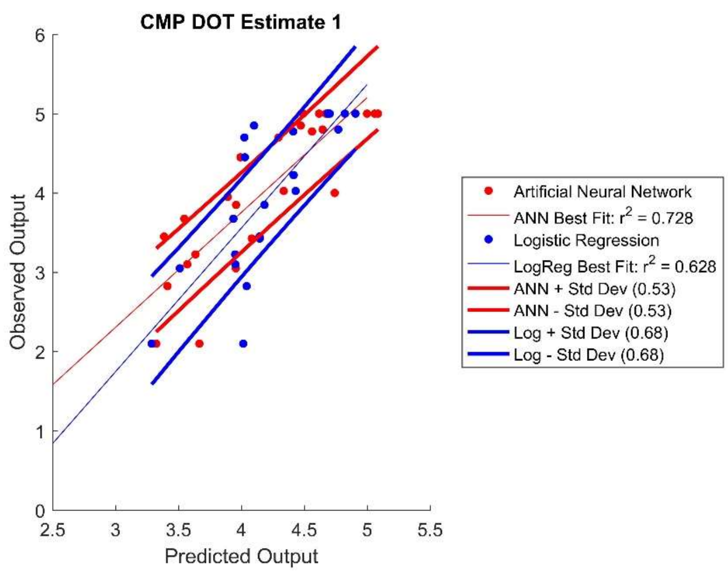


Figure C-3: CMP DOT Estimate 1 Composite Score

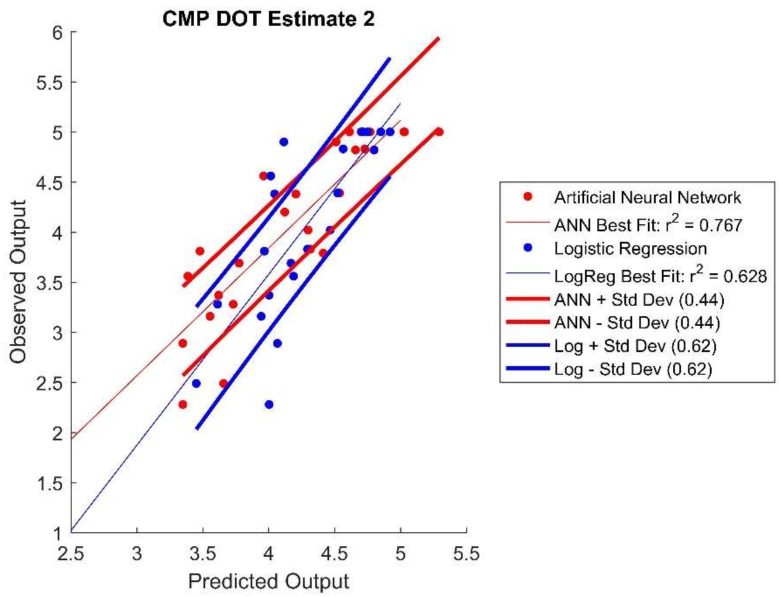


Figure C-4: CMP DOT Estimate 2 Composite Score

The improvement in the coefficient of determination for the models with and without age as an additional input is clear. In all cases for both the neural network model and the logistic regression saw a significant improvement in the value of the coefficient of determination. The reason for this increase could be attributed to two reasons. The first reason could be the significant impact of the age information as an input for the model. Because it is the only time-dependent variable used in the model, it is likely that the installation date of the culvert would significantly impact the model. In the logistic regression models where it was easy to determine the coefficients for the model, it was discovered that the coefficient associated with age did not have significantly more impact on the model. That is to say that the absolute value of these coefficients were not much larger than the other inputs even normalized to the range over which the installation age varies (a unit increase in installation date is less significant than a unit increase in pH). The second reason is that the reduced amount of data would lead to a less biased model (explained in weaknesses of model). This is unlikely due to the fact that the distribution of culvert ratings for the culverts with installation date as an input matches the distribution of culvert ratings for the entire database.

The mentioned benefits of the model that included an indication of the age came with some noted weaknesses. The difficulty with which the age information was produced meant that only age information for CMP culverts could be determined. Applying this model to different types of culverts could be suitable, but without additional age information, there would be no way of verifying the model. In addition, it would mean that each model would be useless unless the age of the culvert was produced. With these weaknesses in mind, the final model only incorporates the models produced without age as an input. Further information could produce a model that utilizes age and represents a true deterioration model.

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