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THE UNIVERSITY OF BRITISH COLUMBIA

PREDICTION OF PIPE PERFORMANCE WITH MACHINE LEARNING USING R

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1. Instruction

As one of the most important infrastructures in cities, water mains buried underground require an efficient infrastructure management system to manage complicated deteriorating pipeline systems, since the failure of pipeline can result in high maintenance cost and serious threats to society and the environment. The core component of the management system is the technology for condition assessment of water mains, specifically, methods to evaluate the pipeline condition and methods to predict the pipe's remaining service life. Hence, lots of studies have been undertaken, utilizing data to develop a decision model to assess the pipe performance and analyze the key factors leading to pipeline failure.

For water mains assessment, statistical models are a cost-effective means of analysis. The generalized multivariate exponential model proposed by Kleiner and Rajani et al. (2003) considered time-dependent variables and allows for simple evaluation and variation prediction in pipe breaks. Multivariate exponential model was also developed, compared with transition state-life regression model and validated later (Osman, Ph, & Bainbridge, 2011). Recently, another statistical model: a Bayesian belief network model (BNN) was proposed, which used soil properties to predict the remaining service life of water mains (Demissie, Tesfamariam, & Sadiq, 2014). It determined soil corrosion index by sorting the soil parameters into major groups and minor groups. Then, combining with a mathematical model, the safety index is calculated with pit depth, corrosion initiation time and pipe wall thickness using BBN. Such statistical approaches mentioned above may help pipeline management by predicting remaining service life or break rate of water mains. However, in parallel with the statistical approaches, the complexity of water networks has led to wider employment of data mining techniques to predict pipe failures (Berardi, Giustolisi, Kapelan, & Savic, 2008).

Based on data mining techniques, artificial neural networks (ANN) methods have been widely employed in pipe's performance prediction. To improve previous failure prediction of pipelines, ANN model: multilayer perceptron (MLP) is proposed (Achim, Ghotb, & Mcmanus, 2007). It achieved an improvement 19% in terms of r^2 when compared with shifted time exponential model. Then a model integrated Analytical Hierarchy Process and ANN was developed (Al-barqawi & Zayed, 2008). After utilizing AHP to determine weights of factors and their sub-factors, supervised ANN and back propagation algorithm were used to predict pipe performance and its deterioration rate. Fahmy et al. (2009) applied multiple regression, MLP and general regression neural network (GRNN) to forecast the remaining useful life of cast iron water mains. Considering two rehabilitation strategies: Cement Mortar Lining and Cathodic Protection, Asnaashari et al. (2013) predicted the watermain failure rates successfully using ANN modelling.

However, in a recent study, when GRNN and Feed Forward Neural Networks were used to estimate the pipe failure rates, their performance was worse than that of a novel approach combining fuzzy clustering and least square support vector machine (LS-SVM) (Aydogdu & Firat, 2015). Through the review of previous studies, integrated modelling tends to have a more outstanding prediction performance because they would have the advantages of two or more models. Therefore, this project presents a stacking ensemble prediction method, combining the predictions from different advanced models, to modify existing models. Armed with the tools learnt from the class, this project first used Excel to do data transformation, cleaning and some basic data analysis. Then cleaned data was read into R to do more data visualization and analysis first based on ggplot package. Finally, machine learning was employed to predict the pipe performance based on the caret package in R.

2. Data Description

The original dataset is a xlsx file which contains 119 rows and 19 columns data with missing values and irrelevant variables. These datasets of water mains were collected from Toronto (Doyle, 2000) including pipe identity, external pit depth, internal pit depth, pipe age, pipe wall thickness and five soil properties.

3. Overview of Techniques

Based on the techniques covered in the class, Microsoft Excel and R were selected in this project. Microsoft Excel is the most popular spreadsheet program that allows users to quickly sort, analyze and report data. In this project, Excel was used to do data transformation and data cleaning. For R, it is an open source programming language for statistical computing and graphics with the most comprehensive available statistical analysis package. Since the graphical capabilities of R are outstanding, it was utilized to visualize data based on the ggplot package in this project. With respect to machine learning, the caret package in R offers a nifty way of developing it. In addition, since the new technology and ideas often appear first in R, ensemble method implemented was based on the latest package in R, caretEnsemble.

4. Data Cleaning Using Excel

Because of the difficulty of collecting data related to soil properties and pipe features, shown as Fig.1, the dataset I obtained is full of missing values. Therefore, I first used Excel to replace missing values with NA() function and color these cells with conditional formatting function, which is shown as Fig. 2. Finally, the aggregate functions are used to create new and more useful variables. Fig.3 presents the final cleaned data.

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1		Pit Depth Measurements								Soil Properties				
2		Exterior												
3	ID NO.	Pit1	Pit2	Pit3	Pit4	Pit5	Thickness	Age	break(y/n)	Sulphide Concentration	PH	Resistivity	Soil ID	Moisture
4		[mm]	[mm]	[mm]	[mm]	[mm]	[mm]	[Years]		[mg/kg dry soil]		[ohms.cm]		Content
5	1	0	0	0	0	0	10.7	124	Y	1.05	9.4	2892	CH/MH(maybe OH)	21
6	2	3.6	2.7	2.4	2.2	1.6	11.7	105	Y	1.92	8.7	2882	SP-SM	23
7	3	5	6.2	5.2	3.5	3.3	11.1	88	Y	0.53	8.8	14946	SP	23
8	4	0	0	0	0	0	14.4	75	Y	0.81	9.5	948	CL/ML	25
9	5	2.7	3.4	3.4	4	2.5	11.5	90	Y					
10	6	10.7	10.7	10.7	10.7	6.6	10.7	122	Y	0.25	8.7	545	CH/MH	14.6
11	7							122	Y					
12	8	7.4	4.4	6.3	4.4	5.3	11	26	Y					
13	9	0	0	0	0	0	9.8	93	N	0.20	9.2	1973	SC	14.6
14	10	0	0	0	0	0	12.6	109	N					
15	11	2.7	2.2	3	1.9	2.2	12.1	108	N	0.18	8.6	5252	SP-SM	5.4
16	12	2.7	2.3	1.6	1.4	1	10.6	93	N	0.46	9.1	1498	CL	19
17	13	4.8	2.5	4.7	2.5	1.3	12	80	N	0.28	7.8	13860	SP-SM	8.4
18	14	0	0	0	0	0	13.9		Y	0.19	9.0	6000	SC	12.4
19	15	4.7	3.7	3	3.2	4	12	121	Y					
20	16	13	6.4	8.5	7.7	5.3	13	121	Y					
21	17	3.9	4.2	2.7	3.6	4.2	9.9	86	N	0.34	8.7	13860	SC	8.9
22	18	2.9	2.9	2.1	2.1	1.8	11.8	121	Y	0.21	9.5	1460	ML/SM	18.3

Fig. 1. Spreadsheet of raw data

	A	B	C	D	E	F	G	H	I	J	K	L	M	N
1	ID NO.	Age	break(y/n)	Thickness	Pit1	Pit2	Pit3	Pit4	Pit5	Sulphide Concentration	PH	Resistivity	Soil ID	Moisture
2		[Years]		[mm]	[mm]	[mm]	[mm]	[mm]	[mm]	[mg/kg dry soil]		[ohms.cm]		Content
3	1	124	Y	10.7	0	0	0	0	0	1.05	9.4	2892	CH/MH(maybe OH)	21
4	2	105	Y	11.7	3.6	2.7	2.4	2.2	1.6	1.92	8.7	2882	SP-SM	23
5	3	88	Y	11.1	5	6.2	5.2	3.5	3.3	0.53	8.8	14946	SP	23
6	4	75	Y	14.4	0	0	0	0	0	0.81	9.5	948	CL/ML	25
7	5	90	Y	11.5	2.7	3.4	3.4	4	2.5	#N/A	#N/A	#N/A	#N/A	#N/A
8	6	122	Y	10.7	10.7	10.7	10.7	10.7	6.6	0.25	8.7	545	CH/MH	14.6
9	7	122	Y	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A	#N/A
10	8	26	Y	11	7.4	4.4	6.3	4.4	5.3	#N/A	#N/A	#N/A	#N/A	#N/A
11	9	93	N	9.8	0	0	0	0	0	0.20	9.2	1973	SC	14.6
12	10	109	N	12.6	0	0	0	0	0	#N/A	#N/A	#N/A	#N/A	#N/A
13	11	108	N	12.1	2.7	2.2	3	1.9	2.2	0.18	8.6	5252	SP-SM	5.4
14	12	93	N	10.6	2.7	2.3	1.6	1.4	1	0.46	9.1	1498	CL	19
15	13	80	N	12	4.8	2.5	4.7	2.5	1.3	0.28	7.8	13860	SP-SM	8.4
16	14	#N/A	Y	13.9	0	0	0	0	0	0.19	9.0	6000	SC	12.4
17	15	121	Y	12	4.7	3.7	3	3.2	4	#N/A	#N/A	#N/A	#N/A	#N/A
18	16	121	Y	13	13	6.4	8.5	7.7	5.3	#N/A	#N/A	#N/A	#N/A	#N/A
19	17	86	N	9.9	3.9	4.2	2.7	3.6	4.2	0.34	8.7	13860	SC	8.9
20	18	121	Y	11.8	2.9	2.9	2.1	2.1	1.8	0.21	9.5	1460	ML/SM	18.3

Fig. 2. Spreadsheet of raw data with missing value highlighted

	A	B	C	D	E	F	G	H	I
1	ID	age	breakYN	sulphide	ph	resistivity	moisture	soilType	maxPit
2	2	105	Y	1.92	8.7	2282	23	Sand	3.6
3	3	88	Y	0.53	8.8	14946	23	Sand	6.2
4	6	122	Y	0.25	8.7	545	14.6	Clay	10.7
5	11	108	N	0.18	8.6	5252	5.4	Sand	3
6	12	93	N	0.46	9.1	1498	19	Silt	2.7
7	13	80	N	0.28	7.8	13860	8.4	Sand	4.7
8	17	86	N	0.34	8.7	13860	8.9	Clay	4.2
9	18	121	Y	0.21	9.5	1460	18.3	Clay	2.9
10	19	89	Y	6.66	8.7	424	30.1	Silt	1.5
11	21	85	N	0.5	8.9	36.2	20	Clay	11
12	24	86	N	0.38	8.2	1683	9.5	Clay	3.2

Fig. 3. Spreadsheet of cleaned data

5. Data Visualization and Analysis Using R

One key factor results in the water mains' failure is the corrosion of the pipelines. Corrosion is classified into two types: internal corrosion caused by water flowing through the pipe and external corrosion caused by the soil surrounding the pipe (Doyle, 2000). The most direct results of corrosion are the corrosion pits in pipes structure. With the data of break history and depth values of external maximum pits of the water mains, Fig. 4 illustrates that the pipes with break history have much higher maximum pit values, which indicates that it is the external corrosion that results in pipe failure indirectly.

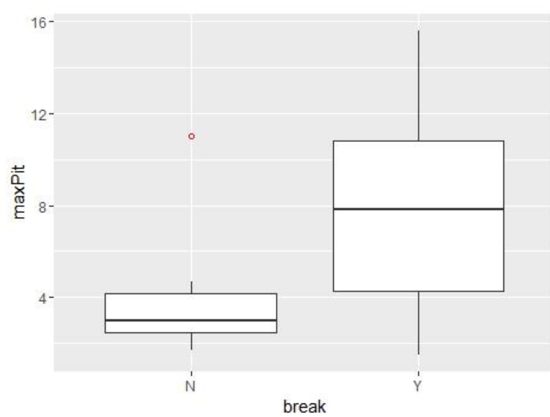


Fig. 4. Pit depth vs. break history

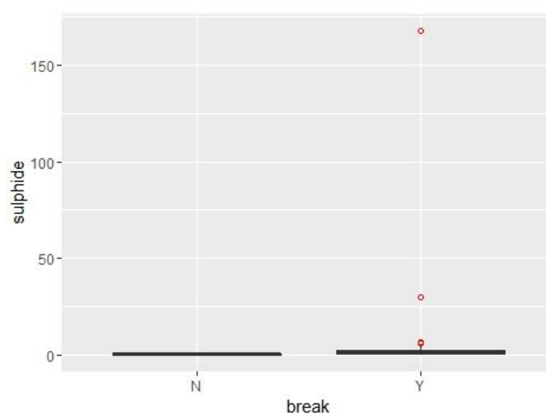
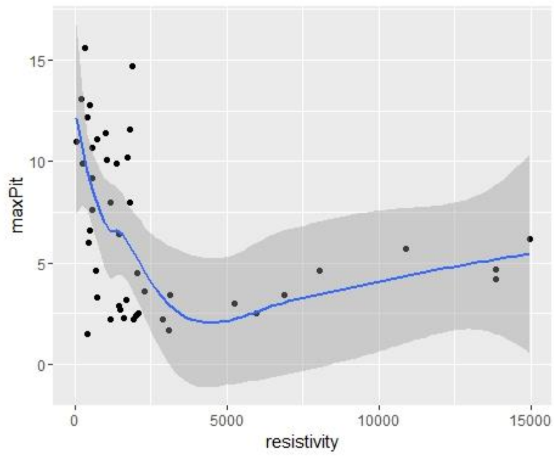


Fig. 5. Sulfide vs. break history

Through the direct contact of pipes, soil environment causes pipe corrosion mainly by electrochemical reactions including galvanic corrosion cells, electrolytic corrosion cells, bacterial corrosion, acid attack etc. (Doyle, 2000). Because soil environment with high sulfide contents would promote the growth of the sulfite reducing bacteria which can cause bacterial corrosion, the few soil data with high sulfide contents were shown in Fig. 5 as outliers.



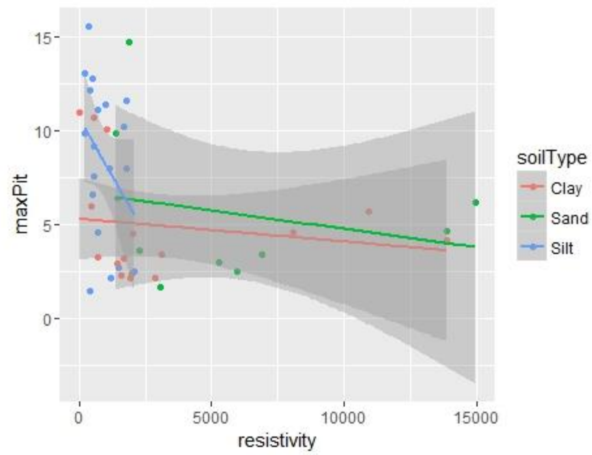
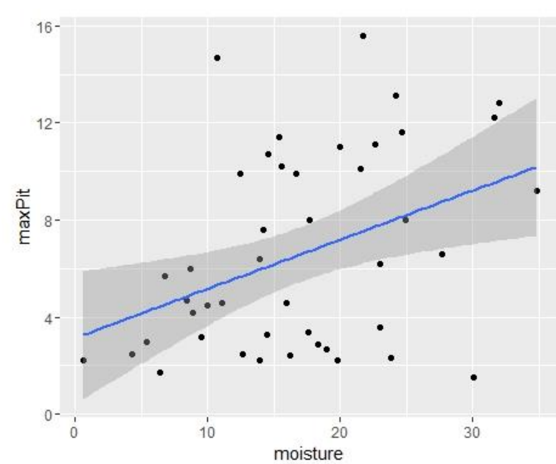


Fig. 6. Pit depth vs. resistivity **Fig. 7.** Pit depth vs. resistivity with soil type labels

For electrochemical corrosion, soil resistivity is the main factor in determining deterioration rate. Commonly, with the reduce of resistivity, the deterioration rate of pipes increases, which is shown in Fig. 6. In addition, the soil resistivity is closely related to the soil type. Fig. 7 shows that the resistivity in silt soil is low, which may result in the highest value of pit depth of pipes in silt soil environment. Apart from resistivity, soil moisture content is the main factor determining the corrosion current density (Cole & Marney, 2012). As shown in Fig. 8, the higher the moisture content is, the more corrosive the soil environment is. Furthermore, Fig.9 presents that silt soil has highest moisture contents, which may be another reason for that the silt soil is the most corrosive. However, the scientific correlation between moisture content and corrosion has not been established and proved.



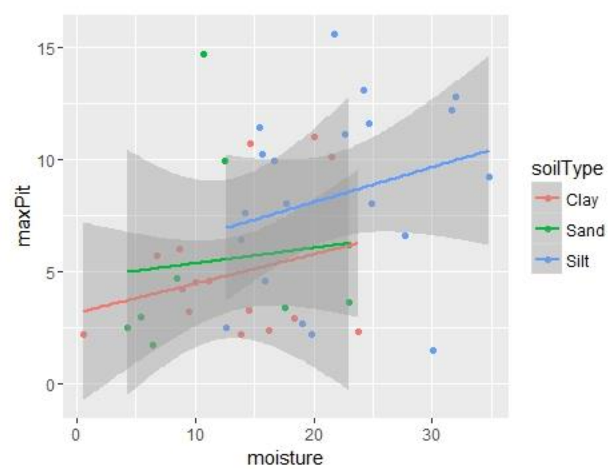


Fig. 8. Pit depth vs. moisture **Fig. 9.** Pit depth vs. moisture with soil type labels

6. Prediction of Pipe Performance Using R

With the collected data, soil properties were considered in this prediction modelling, which were summarized in Table 1. Important statistical information such as mean, median and quartiles was provided. As shown in Table 1, the value of resistivity is much larger than other variables, which should be regularized, so the log of resistivity is used in machine learning finally.

Table 1. Summary of Data of Soil Properties Used in Experiment

Soil Properties	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
Resistivity (Ω cm)	36.2	578.0	1498.0	2815.4	2282.0	14946
PH value	7.20	8.40	8.70	8.68	9.00	10.50
Sulfide	0.00	0.38	0.76	5.71	1.92	167.88
Moisture	0.60	11.10	16.20	16.94	22.60	34.80
Soil Type	Sand	9	Clay	16	Silt	20

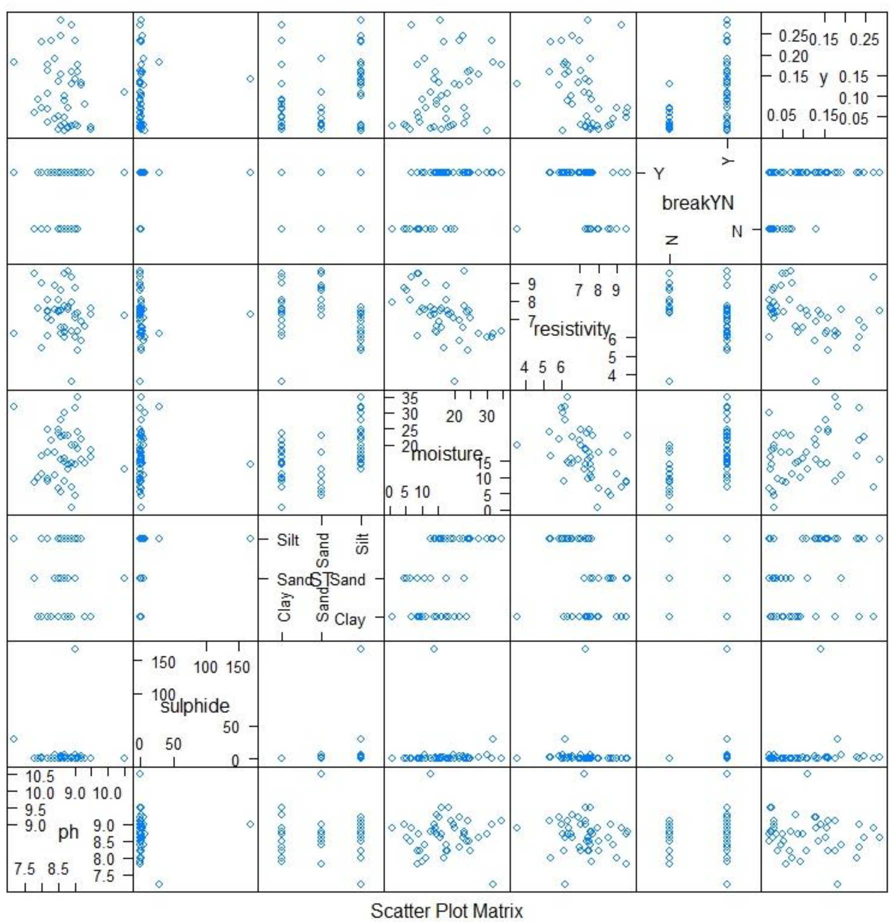


Fig.10. Scatter plot matrix for variables and the target

To evaluate pipe condition, pipe deterioration rate (DR) was used as the predictive target in this experiment, which was expressed as the ratio between the maximum pitting depth and pipe age (Liu, Sadiq, Rajani, & Najjaran, 2010). Then, corresponding scatter plot with the DR as y was shown in Fig. 10, which provided an overview of the relationship between every two variables. As depicted in Fig.10, the plot relating DR to pH are scattered randomly, which may indicate there is no strong correlation between the soil pH and DR.

6.1 Random Forest (RF)

RF gets its name from the concept that each tree is grown with a randomized subset of predictors, and that a forest consists of a large number of trees (Liu et al., 2010). It starts with a standard machine learning technique, decision tree. Not only does it has fast runtimes, but it also can deal with unbalanced and missing data. However, it also has disadvantage that when it is used for regression, it may overfit datasets that are particularly noisy. As an ensemble method, the random forest was first tried in this project.

6.2 Gaussian Process

A Gaussian process is a collection of random variables that have joint Gaussian distributions, which can be employed as a supervised learning method to solve flexible non-linear regression problems. The appearance of kernel machines such as SVM and Gaussian opens the new perspectives with practical prediction and nonlinear modeling (Rasmussen, 2006). Therefore, Gaussian process with a radial basis function (RBF) kernel model was built in this study to help predict DR of pipelines. The RBF kernel is stationary kernel, which can be expressed as following:

$$\kappa(x_i, x_j) = exp\left(-\frac{d(x_i/l, x_j/l)^2}{2}\right) \tag{1}$$

where $\iota > 0$, which is a length-scale hyperparameter (Yang, Smola, Song, & Wilson, 2015).

6.3 SVM

The SVM algorithm derived from a nonlinear generalization of generalized portrait algorithm in 1993 and entered the standard methods toolbox of machine learning in around 1998 (Smola & Schölkopf, 2004). The SVM is scalable, which can generalize well, even on relatively small given training data sets (Suykens & Vandewalle, 2000). The SVM is applied to regression problems by the introduction of an alternative loss function (Brereton & Lloyd, 2010). In this experiment, SVM with a RBF kernel was used to predict the pipe performance. In the training process, two parameters should be noticed: λ and c. λ parameter defines the influence weights of a single training examples while c parameter weights the error of training samples against simplicity of decision surface. After model tuning, the final parameters used for the model were $\lambda = 0.0245517$ and $c = 1$.

6.4 Combine Model Prediction into Ensemble Predictions

Stacking is about combining multiple models built by using different learning algorithm on the same dataset. After a set of base-level models are built and evaluated, a meta-level model is introduced to learn how to combine the results of the base-level models (Dzeroski & Zenko, 2004). Intuitively, ensembles allow the different needs of a difficult problem to be handled by models suited to those particular needs (Oza & Tumer, 2008). In this study, stacking ensemble method used higher-order model, generalized linear model (GLM) to learn how to best combine two best performance models: Gaussian and SVM.

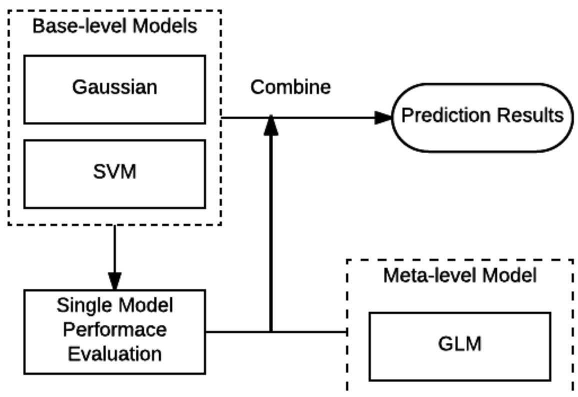


Fig.11. Flowchart of methodology of stacking ensemble

As shown in Fig.11, the first step of ensemble approach was to build Gaussian and SVM models, where the results were evaluated with the square root of the average of the square of all the error (RMSE) and R-squared (R^2). The evaluation results from the ensemble system in the training phase were shown as Fig.12. With the assessment of performance of every single model, as the meta-level model, generalized linear regression (GLM) was trained to learn how to determine the best weights of results obtained from different modeling.

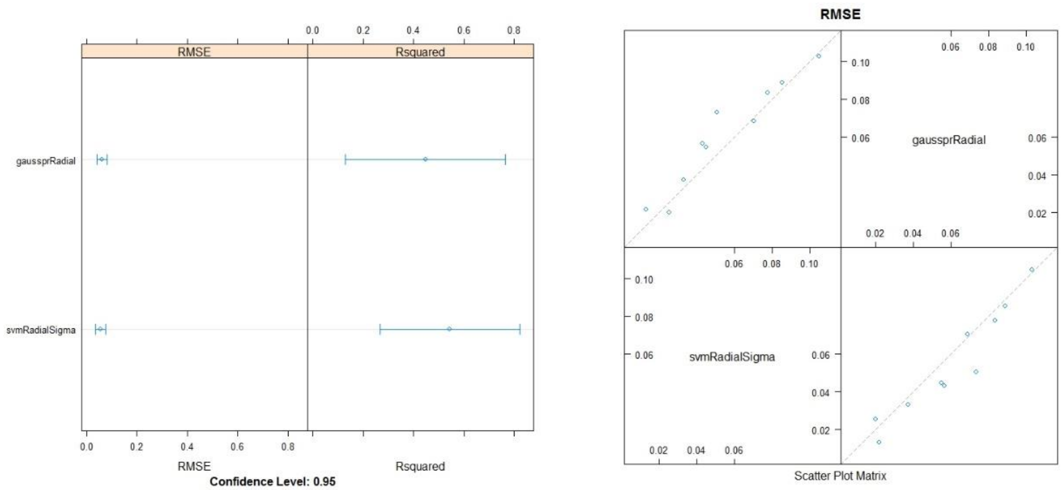


Fig.12. Prediction evaluation of Gaussian and SVM in ensemble

7. Results

In this experiment, the RMSE and R^2 were used to evaluate the prediction performance of different modeling methods. Their equations are as following:

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2} \tag{3}$$

Whereas R-squared is a relative measure of fit, RMSE is an absolute measure of fit. The lower RMSE is, the better the model fits. For R-squared, it ranges from zero to one and the higher value it is (close to 1), the better the model fits. Table 2. Presents the RMSE and R^2 in training and testing phases for all single models and the ensemble model, which demonstrates that the stacking ensemble method has the best performance with the highest R^2 in comparison with to other models.

Table 2. Model Assessment (Best Results Are Highlighted in Bold)

	Model	RF	Gaussian	SVM	**Ensemble**
Train Set	R-Squared	0.483	0.570	0.778	**0.790**
	RMSE	0.0608	0.0558	0.0538	**0.0554**
Test Set	R-Squared	0.525	0.659	0.732	**0.792**
	RMSE	0.0394	0.0333	0.0296	**0.0261**

Even though the data collected is small, the ensemble modeling proposed in this paper still has a good prediction performance with the highest R^2 value of 0.792 and the lowest RMSE value of 0.0261. Compared with Gaussian and SVM modeling, its accuracy of the prediction also has a certain level of improvement.

8. Conclusion

Since the need to assess watermain performance efficiently is growing, forecasting the condition of water main becomes increasingly important. This project employed a novel approach to better forecast the pipe performance based on machine learning with stacking ensemble modeling. Four models including the ensemble model were implemented to predict the condition of pipelines. Compared with the performance of RF, Gaussian and SVM models, the superiority of ensemble methods is demonstrated, reducing the RMSE up to 45%. Since the ensemble modeling developed in this paper is robust and accurate, it can assist pipe management system to do pipe performance measure using data of soil properties.

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