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STUDY ON SOIL MIXTURE STRENGTH DEVELOPMENT FORECASTING BASED ON BP NEURAL NETWORK AND SVM

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ABSTRACT
The strength value is a core indicator in the field of soil stabilization, so evaluating the strength development is a common problem in geotechnical engineering. Compared with the traditional linear fitting method, Machine Learning applied in the engineering field is a more effective and accurate method for fitting and predicting data. The aim of this research was to explore whether the unconfined compressive strength values of soil mixtures can be accurately predicted by machine learning model. Back Propagation Neural Network (BPNN) and Support-vector Machines (SVM) are classical algorithms in the Machine Learning field, and both algorithms will be tested in this research. On the other hand, to improve the precision rate, this research uses an empirical formula to determine the quantity of hidden layers of the Back Propagation model and uses grid searching to find the best penalty factor value and size of mapped dimensions of the SVM. The results showed that both Machine Learning algorithms have higher accuracy, but that SVM has a better performance compared to BPNN: the average R2 value of SVM is 0.94426; the average R2 value of BP NN is 0.94426. It provides a new statistical method for soil performance research in the future.

Keywords:
Machine Learning, BP Neural Network, Support-vector Machines, Soil improvement, Unconfined compressive strength.

INTRODUCTION

Soil is the various sediments generated by the rock's physics, chemistry, weathering as well as denudation, transport, sedimentation, and other complex processes in the natural environment (Zhejiang University, Southeast University, & Hunan University, 2014). Generally, the soil is composed of water, air, and various mineral substances. Due to its complex contents and loose structure, and with the reinforcing agent increasing, the soil's unconfined compressive strength value always shows non-linear growth. Rather than relying on traditional methods, machine learning can be a better method to analyze and predict soil mixture's properties. (Scott Kirts, Orestis P. Panagopoulos, Petros Xanthopoulos, & Boo Hyun Nam, 2018).

Either cement or concrete, on the other hand, can provide high strength to reinforce soil. However, both have high costs and may harm the environment during the production process. While lime, fly ash and blast furnace slag, the cheapest of the energy conservation substances, can be regarded as a similar reinforcing agent as cement and concrete. However, when calculating strength development in these substances, it has its limitations such as loose structure and uneven content. As mentioned above, linear fitting may no longer be suitable for presenting soil mixture strength development. Therefore, instead of a traditional fitting formula, Machine Learning can be used as an approach for solving this problem.

By Phil Kim (2016) mentioned that Machine Learning is a technology that uses data to establish a model. It is a branch of artificial intelligence in which a computer generates rules underlying or based on raw data that has been fed into it. Machine Learning in civil engineering domains has been extensively explored in concrete structure strength prediction and engineering detection, due to its powerful performance of non-linear fitting (Kai Li, Yunpeng Long, Hao Wang,

& Yuan-Feng Wang, 2021). The results show that Machine Learning performs well in the civil engineering field. Most studies investigate the cement or concrete mix with soil, because of its uniform structure and high strength. In this research, Machine Learning will be applied in civil engineering objectives through: (1) To determine what factors affect the physical and mechanical properties of the soil mixture;(2) To determine which types of Machine Learning models have the highest adaptability and generalization in the geotechnical engineering field;(3) To determine if Machine Learning models have higher performance and accuracy than equation fitting.

LITERATURE REVIEW

Machine learning has proven to perform well in engineering. S.KUMAR and P.K. BASUDHAR（2018） established a neural network to predict the stability of slopes by establishing empirical relations for stability coefficients adopting a machine-learning process analyzing available data in the form of tables or charts. Kai Li (2021) uses three types of machine learning models to predict concrete creep, based on BPNN, SVR (support vector regression), and ELM (extreme learning machine). In other research, BPNN can be used to predict laterite's strength when was reinforced by cement, and the precision has high accuracy (Yang Yuting, 2010). However, there is not much research applied to it in the field of geotechnical engineering.

Scott Kirts et al.(2018) created a soil-compressibility prediction model using SVM and he explored the relationship between the compression index (Cc), recompression index (Cr), and the overall settlement. He found that the Cc model for fine grains (clays and silts) is strong and compares well with existing correlations while Cr model could not be obtained. Amit Gajurel (2019) adopted LR (Logistic regression), DA (discriminant analysis), KNN (k-nearest neighbors), and SVM to analyze UCS values which are used to establish the optimum additive amount of chemically stabilized subgrade. The results show that the KNN model has the highest performance compared to the others, and SVM with the radial kernel showed better performance than SVM with the polynomial kernel. Based on previous research, it shows that the generalization ability of machine learning is high in the field of geotechnical engineering. This research uses both BPNN and SVM established models to predict the UCS of soil mixture. The theory of both algorithms will be discussed briefly in Methodology.

METHODOLOGY

Theory of BPNN

Back Propagation Neural Network is one type of Artificial Neural Network (ANN). ANN is a machine-learning system based on the biological nervous system. According to S.KUMAR et al. (2018), ANN consists of a group of neurons logically arranged in multiple layers. These neurons interact through weighted connections. The Back Propagation technique developed by Rumelhart et al. (1986) for multilayer feedforward neural network is based on propagates backward of error. The basic structure of BP neural network is shown in Fig 1.

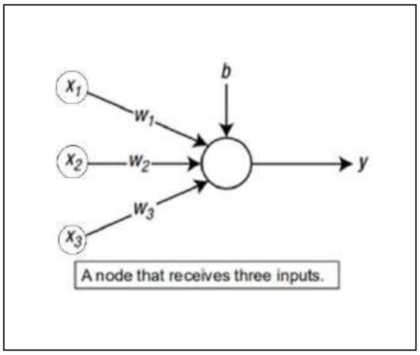

Figure 1: Structure of a Node of BP Neural Network (Lan Goodfellow, 2016)

Fig 1 refers to x1, x2, and x3 are the input signals; w1, w2, and w3 are the weights of the corresponding signals; "b" is the bias. The circle and arrow on the figure represent the node and signal flow. The information from the neural net is stored in the form of weights and biases. The matrix equation of the weighted sum can be expressed as:

$$v = wx + b \tag{1}$$

Where, w and x are represented as:

$$w = \begin{bmatrix} w_1 & w_2 & w_3 \end{bmatrix} \qquad x = \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix} \tag{2}$$

In Fig 2, the group of leftmost nodes is called the input layer. It only inputs data to the model and does not calculate any functions. On the other hand, the group of rightmost nodes in an ANN is called the output layer. The output of these nodes is then the final result of the ANN. The layer between the input layer and output layer is called the hidden layer. According to the number of hidden layers, there are three types of BP Neural Network. The structure as follow:

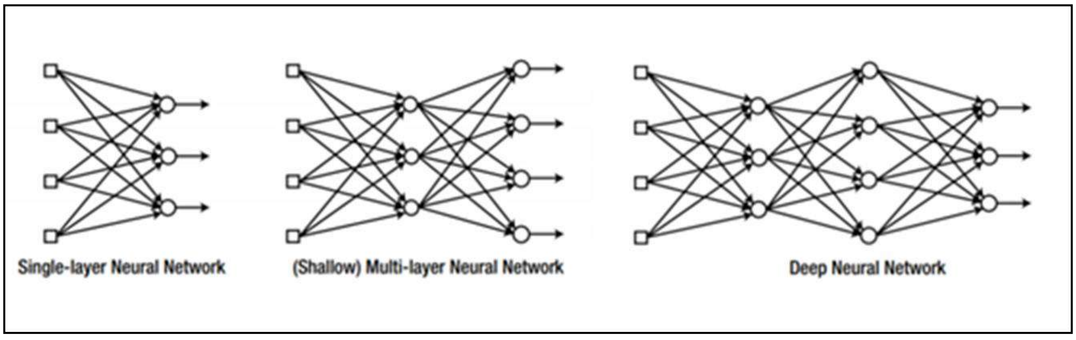

Figure 2: Structure of 3 Types of BP Neural Network (Lan Goodfellow, 2016)

Theory of SVM

The original SVM algorithm was invented by Corinna and Vladimir (1995). SVM provides supervised learning models with associated learning algorithms for analyzing data for classification and regression analysis. Support-vector machines construct a hyperplane or set of hyperplanes in a high dimensional or infinite-dimensional space and can be used for classification, regression, or other tasks like outlier detection, or to identify the underlying vector structure. In classification, the hyperplane with the largest distance to the nearest training data point can achieve positive separation. In general, the larger the boundary, the lower the generalization error of the classifier. The distance between the separate hyperplane and the training data closest to the hyperplane is called the margin. The hyperplane with the maximum margin is called the optimal separating hyperplane. The basic structure of the SVM is shown in Fig 3.

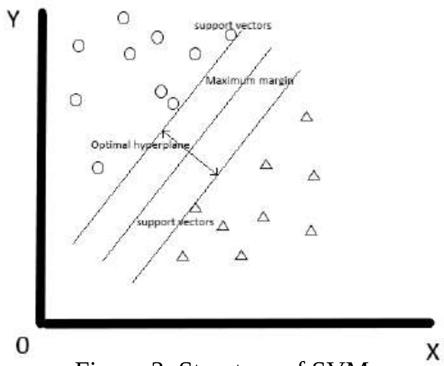

Figure 3: Structure of SVM

The linear regression formula of SVM is:

$$D_x = \mathbf{w}^T \boldsymbol{x} + b \tag{3}$$

Where, w is an d-dimensional vector, b is a bias term, i = 1, . . . , N

$$\mathbf{w}^T \boldsymbol{x_i} + b \begin{cases} > 0 & \text{for } y_i = 1, \\ < 0 & \text{for } y_i = -1 \end{cases} \tag{4}$$

Dataset

This paper collected the previous data from Investigation of Strength and Microstructure of Lime-blast Furnace Slag Stabilized Loess (Zhang Li, 2020). In this dataset, to improve accuracy, the author made one sample of soil mixture with three specimens and a total of 351 samples. This research collects all the data and calculates the average value for each content sample, collecting 117 values in this experiment. All the experiments follow The Standard for Test Methods of Earthworks (GB/T50123-1999). Table1. shows an example of dataset, for sample no.1-no.30(In total, there were 117 samples in this model):

Table 1: Example of Dataset for Sample No.1-No.30 (Zhang Li, 2020)

Number	Lime(%)	Blast Furnace Slag(%)	Loess(%)	Dry Density(g/cm^3)	Moisture Content(%)	Date(day)	Unconfined Compressive Strength(kp$_a$)	Internal Friction Angle(°)	Cohesive Force(kpa)	Splitting Tensile Strength(kpa)
1	9	1	90	1.63	17.18	3	209.1	46.91	65.8	9.26
2	9	1	90	1.63	17.18	5	244.9	46.91	71.51	23.19
3	9	1	90	1.63	17.18	7	271.11	46.91	77.65	25.51
4	9	1	90	1.63	17.18	28	490.79	46.91	119.08	44.69
5	9	1	90	1.63	17.18	90	967.7	46.91	279.09	99.47
6	9	1	90	1.63	17.18	180	1130.7	46.91	345.68	141.83
7	9	1	90	1.63	17.18	365	1463.18	46.91	Nan	Nan
8	7	3	90	1.66	17.18	3	533.03	46.91	151.34	46.33
9	7	3	90	1.66	17.18	5	622.76	46.91	158.19	55.61
10	7	3	90	1.66	17.18	7	634.24	46.91	167.13	56.9
11	7	3	90	1.66	17.18	28	764.26	46.91	204.04	72.33
12	7	3	90	1.66	17.18	90	1289.32	46.91	360.05	134.78
13	7	3	90	1.66	17.18	180	1489.12	46.91	*397.09*	*149.57*
14	7	3	90	1.66	17.18	365	1981.96	46.91	Nan	Nan
15	5	5	90	1.68	17.18	3	678.38	46.91	193.48	58.89
16	5	5	90	1.68	17.18	5	755.89	46.91	197.7	70.65
17	5	5	90	1.68	17.18	7	852.36	46.91	232.22	76.04
18	5	5	90	1.68	17.18	28	1070.46	46.91	273.46	95.52
19	5	5	90	1.68	17.18	90	2010.63	46.91	567.38	201.83
20	5	5	90	1.68	17.18	180	2248.56	46.91	600.29	269.97
21	5	5	90	1.68	17.18	365	2547	46.91	Nan	Nan
22	18	2	80	1.58	18.37	3	719.18	46.91	199.65	65.96
23	18	2	80	1.58	18.37	5	869.42	46.91	217.65	78.21
24	18	2	80	1.58	18.37	7	954.26	46.91	238.17	84.29
25	18	2	80	1.58	18.37	28	1090.12	46.91	294.28	100.06
26	18	2	80	1.58	18.37	90	1720.13	46.91	475.23	179.3
27	18	2	80	1.58	18.37	180	1854.96	46.91	502.69	207.1
28	18	2	80	1.58	18.37	365	2282.19	46.91	Nan	Nan
29	14	6	80	1.6	18.37	3	1032.88	46.91	273.38	91.68
30	14	6	80	1.6	18.37	5	1217.34	46.91	282.13	108.67

In this paper, the trial-and-error method is used to segment the dataset for training and testing and the optimal proportion of this combination is found to be 70% versus 30%. In model training, this paper randomly chooses 70% of the data regarded as training data.

Data Analyzing

Through data analysis, this research can explore and understand the relationship between each element. This paper calculates the correlation coefficient for determining the hidden information in the dataset. The correlation coefficient of these two random variables is a measure of their linear dependence. If each variable has N scalar observations, then the Pearson correlation coefficient is defined as:

$$\rho(A,B) = \frac{1}{N-1}\sum_{i=1}^{N}\left(\frac{\overline{A_i - \mu_A}}{\sigma_A}\right)\left(\frac{B_i - \mu_B}{\sigma_B}\right), \tag{5}$$

Where "μA" and "σA" are the mean and standard deviation of A, and "μB" and "σB" are the mean and standard deviation of B. The correlation coefficient matrix of two random variables is the correlation matrix coefficients for each pairwise variable combination:

$$R = \begin{pmatrix} \rho(A,A) & \rho(A,B) \\ \rho(B,A) & \rho(B,B) \end{pmatrix}. \tag{6}$$

Since ρ(A,A) and ρ(B,B) are always directly correlated to themselves, the diagonal term are only 1, that is:

$$R = \begin{pmatrix} 1 & \rho(A,B) \\ \rho(B,A) & 1 \end{pmatrix}. \tag{7}$$

Model Establishing

This paper uses MATLAB2020 to establish BP neural network model, SVM model and equation linear-fitting model.

Step of BP Neural Network

In general, the main steps for application of the ANN model are data collection, normalization, determining the number of hidden layers and neurons, choice of activation function as well as training data and validation leading to error minimizing and avoidance of over-fitting.

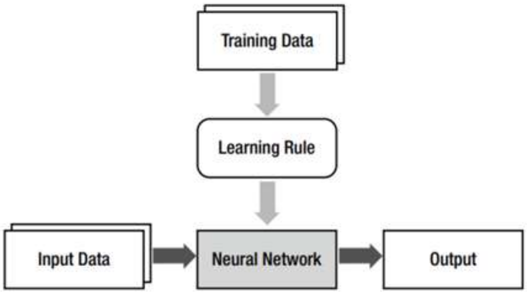

Figure 4: Structure of Neural Network (Lan Goodfellow, 2016)

According to Lan Goodfellow(2016), the deeper the model, the higher the generalization for various tasks. It means that using a deep architecture does express a useful prior over the space of functions in model. This paper uses an empirical equation to determine the value range of hidden layers (GUO Haitao,2000):

$$K < \sum_{i=0}^{n} C_J^i \tag{8}$$

$$J = \log_2 n \tag{9}$$

$$J = \sqrt{n + m} + a \tag{10}$$

Where J is the number of units in hidden layer; K is the number of samples; n is the number of units in input layer; for Cji ,if i>J, Cji = 0; m is the number of units in output layer, α is a constant from 1 to 10. Through repeated testing, this paper sets one hidden layer in this model, and the size of units in the hidden layer is 9.

Step of SVM

The main steps of an SVM are data collection, normalization, determining the best quantity of penalty factor and mapped dimension, choice of activation function as well as training data. This paper sets gamma in the kernel function and uses grid searching to find the best penalty factor value and size for mapped dimensions.

International Journal of Infrastructure Research and Management
Vol. 9 (2), December 2021, pp. 82 - 93

Step of Equation Linear-Fitting Model Establishing

In this paper, the polynomial function is regarded as the approximation function, and on the other hand, this model uses the least square method to minimize errors. Under different soil mixture content, this paper builds a model based on soil mixture strength development and maintenance time. This paper takes values of 180 days from the dataset and uses them to test the accuracy of the model.

RESULTS AND DISCUSSION

Correlation Coefficient Value Result

This research uses MATLAB2020 to implement the algorithm and gets the result as follow:

Table 2: Correlation Coefficient Value

lime	1.00000	0.05393	-0.85096	-0.99268	0.83150	-0.00000	0.16559	0.13735	0.13550
blast furnace slag	0.05393	1.00000	-0.57035	-0.00919	0.55731	0.00000	0.71774	0.67018	0.64949
loess	-0.85096	-0.57035	1.00000	0.82141	-0.97713	-0.00000	-0.51374	-0.46549	-0.45309
dry density	-0.99268	-0.00919	0.82141	1.00000	-0.81448	0.00000	-0.12869	-0.10146	-0.10076
moisture content	0.83150	0.55731	-0.97713	-0.81448	1.00000	0.00000	0.48306	0.43428	0.42669
date	-0.00000	0.00000	-0.00000	0.00000	0.00000	1.00000	0.55581	0.60563	0.63944
UCS	0.16559	0.71774	-0.51374	-0.12869	0.48306	0.55581	1.00000	0.99488	0.98055
CF	0.13735	0.67018	-0.46549	-0.10146	0.43428	0.60563	0.99488	1.00000	0.98349
STS	0.13550	0.64949	-0.45309	-0.10076	0.42669	0.63944	0.98055	0.98349	1.00000
	lime	blast furnace slag	loess	dry density	moisture content	date	UCS	CF	STS

The correlation coefficient value shown above was transformed into a heat map, the details as follows:

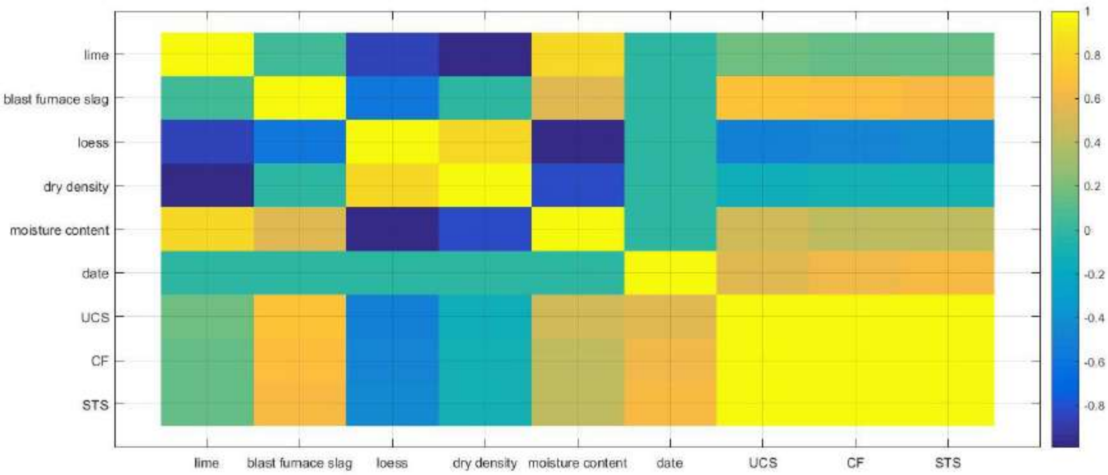

Figure 5: Heat Map of Soil Mixture Features

Where UCS is the unconfined compressive strength value; CF is the cohesive force value; STS is the splitting tensile strength value.

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Model Result

Through machine learning models and equation fitting models established and tested, this paper gets the following results:

Machine Learning Model

Table 3: Comparison of R^2

R^2 of prediction											
Test number	1	2	3	4	5	6	7	8	9	10	11
BP	0.74941	0.7506	0.9463	0.874	0.9823	0.8724	0.9689	0.9005	0.9757	0.9279	0.8626
SVM	0.96027	0.85598	0.9348	0.971	0.95652	0.92344	0.89117	0.95662	0.97132	0.94552	0.94862
Percentage of error(%)	28.14%	14.04%	1.22%	11.10%	2.62%	5.85%	8.02%	6.23%	0.45%	1.90%	9.97%

Table 4: Comparison of R^2

Test number	12	13	14	15	16	17	18	19	20	Maximum Value	Average Value
BP	0.9824	0.9531	0.9534	0.9699	0.8159	0.743	0.9119	0.9823	0.9831	0.9831	0.9053
SVM	0.96575	0.99395	0.96781	0.97481	0.93437	0.87915	0.96789	0.96074	0.92556	0.99395	0.94426
Percentage of error(%)	1.69%	4.29%	1.51%	0.51%	14.52%	18.32%	6.14%	2.19%	5.85%	1.10%	4.30%

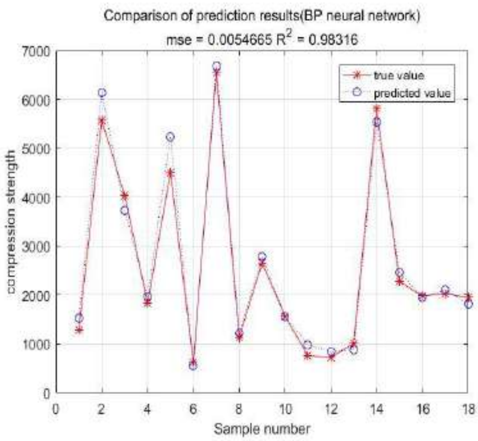

Figure 6: Prediction Result of BP Neural

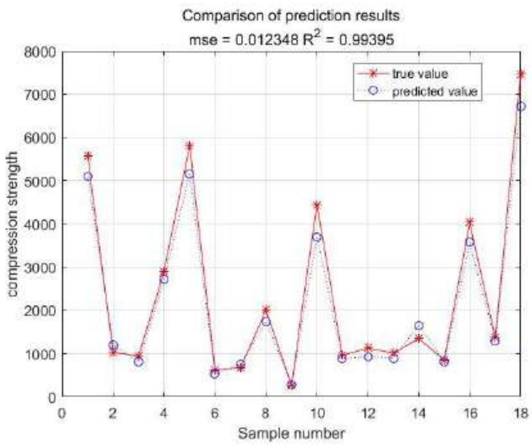

Figure 7: Prediction result of SVM

International Journal of Infrastructure Research and Management
Vol. 9 (2), December 2021, pp. 82 - 93

Equation Linear-Fitting Model

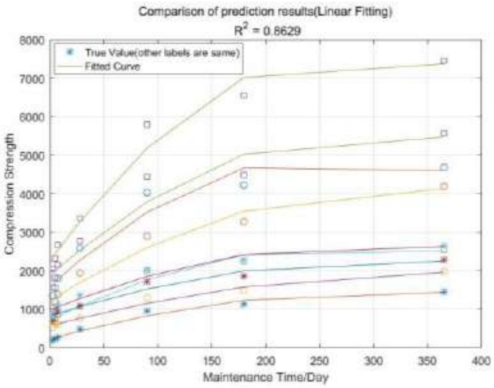

Figure 8: Prediction Result of Equation Linear-

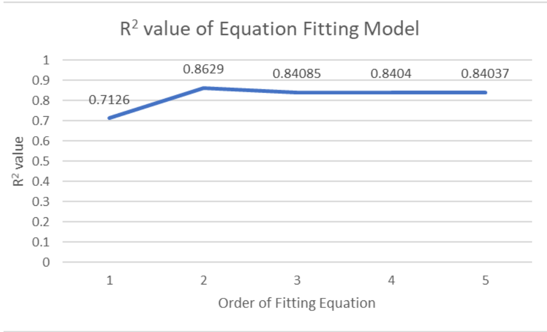

Figure 9: R^2 Value of

Where, R^2 is coefficient of determination, the formula as follow:

$$R^2=1-RSS/TSS \tag{11}$$

$$\text{RSS (Root-Sum-Squares)} = e_1{}^2+e_2{}^2+\ldots+e_n{}^2 = \sum(y_i - \hat{y}_i)^2 \; ; \tag{12}$$

$$\text{TSS (Total Sum of Squares)} = \sum(y_i - \bar{y}_i)^2. \tag{13}$$

The formula of error percentage as follow:

$$\text{Percentage of error} = (\,|\,R^2 \text{ of BP- } R^2 \text{ of SVM}\,|\,) / R^2 \text{ of BP} *100\% \tag{14}$$

DISCUSSION

From this Fig 5, some hidden information can be found: (1) There is a very high correlation between UCS, CF and STS, because CF and STS grow with the growth of UCS ;(2) The correlation coefficient between lime and UCS is very low, while blast furnace slag is high. It means that blast furnace slag plays a dominant role in soil mixture strength development. This is in agreement with Zhang Li (2020); (3) The Loess shows a negative correlation with UCS, which means that with an increase in loess, the UCS of the soil mixture gradually declines. Moreover, the "Date" has zero correlation with soil mixture properties except UCD, CF, and STS, which is consistent with our theoretical understanding (Saeid, et al, 2018).

This paper establishes two machine learning models and randomly chooses the same training data running both models 20 times, getting a coefficient of determination (R2) values. The closer the R2 close is to 1, the less error there is. As shown in Table 3 and Table 4, using machine learning methods to predict soil mixture is feasible in practice. On the one hand, due to most the percentage errors having an absolute value less than 20%, it means that unconfined compressive strength values of soil mixture can be predicted and both models have the same predicted trends (Abd Manan, et al,2021). On the other hand, through comparison, SVM has more accuracy than BP neural network in one single sample. The BP neural network's highest R2 value is 0.9831(Fig 4.), while the lowest R2 is value only 0.743. A possible reason is that under different training data, BP neural network may more easily trap into local optimality or may more easily trap into overfitting than SVM.

In addition, SVM presents better stability than BP neural network in that SVM has a higher average value of R2 than BP neural network. One possible reason is that SVM has more generalization abilities than BP neural network. In summary, SVM has better performance than the BP neural network in this research, where the highest R2 value is 0.99395(Fig 5).

For linear-fitting model results, regardless of whether a BP neural network or SVM is used, the machine learning model has more accuracy than the equation linear-fitting. Fig 6 is the result of second-order equation fitting, and R2 is only 0.8629. Fig 7 shows the R2 value of each order fitting equation which shows that second-order equation fitting has the highest accuracy of prediction.

CONCLUSION

This research analyzes machine learning applied in the civil engineering field and does a series of experiments to prove that machine learning performs well in soil mixture strength prediction. Through correlation coefficient calculations, this research determines that the main element of soil mixture development is blast furnace slag. Through model result comparison, SVM has the best performance, whatever in predicting accuracy or generalization ability. Moreover, both machine learning models have higher R2 values than the equation linear-fitting. Therefore, based on the above research, the machine learning method can be regarded as a better method than equation linear-fitting to predict compressive strength values or other soil mixture property values.

RECOMMENDATION

In this research, the BP neural network has low accuracy and stability, due to the local optimality problem and overfitting problem. In future research, people could combine the BP neural network with a series of optimization algorithms, such as ant colony optimization, Particle Swarm Optimization, and simulated annealing algorithms, to enhance the local optimum and overfitting problems.

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