http://journal.uir.ac.id/index.php/JGEET

E-ISSN : 2541-5794
P-ISSN : 2503-216X

Journal of Geoscience,
Engineering, Environment, and Technology
Vol 9 No 1 2024

RESEARCH ARTICLE

Sensitivity Analysis Based on Physical Properties to Permeability Coefficient of Cohesive Soil Using Artificial Neural Network

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Received: Jul 1, 2023; Accepted: Mar 7, 2024.
DOI: 10.25299/jgeet.2024.9.1.13536

Abstract

Permeability is the ability of a soil to allow liquids to pass through. Of course the soil has a physical characteristic that can be known by laboratory testing. This study aims to determine the physical properties that most affect the coefficient of cohesive soil permeability using the Artificial Neural Network (ANN) tool, the results obtained will later be matched with actual conditions according to the context of engineering geology. The research method begins with an influence or sensitivity analysis using ANN which will produce a correlation coefficient (R). Then, these results will be compared with the influence analysis based on the value of the coefficient of determination (R^2). After that, accuracy and error tests will be carried out using the Mean Absolute Percentage Error (MAPE), the highest accuracy values is categorized as the most influential physical property of the 7 physical property parameters, namely liquid limit, plastic limit, plasticity index, %sand, %fines, %silt, and %clay. Based on the result of the analysis, %fines is the parameter that most influences permeability and is able to make very strong predictions with an R value using an ANN of 0.9941875, an R^2 value of 0.6336, an accuracy of 99.6962%, and a MAPE of 0.3038%. These results are compared with the existing empirical equations with an accuracy of 96.4393% and MAPE of 3.5607%. It can be concluded that ANN is more effective and optimal in making predictions. In this case, in the context of engineering geology, the more %fines, the smaller the permeability coefficient of the soil.

Keywords: *ANN, AI, Permeability, Soil Physical Properties.*

1. Introduction

In the world of geotechnical engineering, soil has a very important role. Apart from being a buffer, soil can also function as the constrcution material itself (Padagi et al., 2015). Planning a good construction requires some testing of soil data such as physical and mechanical properties, the data is obtained of the results of soil investigations in the field and in the laboratory (Naim et al., 2019). Soil is a porous medium through which liquid can pass. Of course, this soil has physical properties that can be known by several tests. For example, atterberg limit and grainsize. Soil permeability is one of the parameters of soil physical properties to predict the movement of water in the soil (Maharani et al., 2015). Permeability is the ability of a soil to pass fluid. Permeability will be smaller if the pore space in the soil particles is filled so that the pore space will be smaller (Yantrapalli et al., 2018).

Recently Artificial Neural Networks (ANNs) have become a popular and useful model for classification, clustering, pattern recognition, and prediction in many disciplines (Abiodun et al., 2018). According to Amanda, (2022) research the empirical correction model of physical properties with soil permeability using ANN (Artificial Neural Network) with the results of a very strong correlation coefficient (R). This means that there is a relationship between physical properties and soil permeability using parameters liquid limit (LL), plastic limit (PL), plasticity index (PI), %sand, %fines, %silt, and %clay. However, the research has not explained the most influential parameters so as to produce a very high R or produce a very strong relationship. In this research, it will be developed from Amanda, (2022) research, namely analyzing the physical properties parameters that have the most influence on the permeability coefficient of cohesive soil with the ANN tool.

The use of Artificial Neural Networks (ANNs) as an approach for permeability modeling in soil offers several advantages over traditional methods. The background and significance of utilizing ANN for this purpose can be explained as follows:

1. Nonlinearity: Soil permeability is a complex parameter influenced by various factors such as soil type, grain size distribution, compaction, and organic content. ANNs are well-suited for capturing nonlinear relationships and patterns in data, allowing them model the intricate relationships between these influencing factors and permeability accurately.
2. Data-driven approach: ANNs excel at learning from data patterns and making predictions based on the learned knowledge. By training an ANN with a substantial dataset of soil properties and corresponding permeability values, the model can identify hidden correlations and patterns that may not be easily captured by traditional analytical models. This data-driven approach enhances the accuracy and reliability of permeability predictions.

3. Flexibility and adaptability: ANN models can be easily adjusted and fine-tuned to accommodate various soil types and conditions. They have the ability to generalize well from training data to predict permeability for unseen soil samples. This flexibility makes ANNs a versatile tool that can be applied across different soil types and locations, making them applicable in a wide range of geotechnical engineering projects.
4. Time and cost efficiency: Conducting laboratory experiments or filed tests to measure permeability can be time-consuming and costly. By developing an ANN-based model, researchers can expedite the prediction process and reduce the reliance on extensive experimental campaigns. This saves both time and resources, making the permeability modeling more efficient and practical.

The research focusing on using ANN for permeability modeling in soil is important and applicable because it addresses the challenges faced by traditional anlalytical models. By harnessing the power of machine learning and data-driven approaches, ANN models provide a more accurate and efficient way to estimate soil permeability. This has significant implications for various geotechnical engineering applications, including groundwater flow analysis, soil remediation, slope stability assessment, and designing effective drainage systems. Ultimately, the utilization of ANNs in permeability modeling contributes to improved engineering designs, cost-effective solutions, and sustainable infrastructure development.

2. Literature Review

Soil is a material consisting of solid mineral aggregates that are not bound to each other from decomposed organic matter accompanied by liquids and gas that fills the pore spaces (Rochmawati et al., 2020). Soil has various physical property tests such as atterberg limit, grainsize, and also has mechanical property tests such as permeability. The size of soil particles varies greatly with considerable variation. Soils can generally be referred to as gravel, sand, silt, and clay, depending on the size of the particles that are most dominant in the soil (Das, 1995).

The atterberg limits consist of LL, PL, and PI. The LL is defined as the limit of water content in the transition state between liquid and plastic. The PL is defined as the limit of water content in the transition state between plastic and semi-plastic. PI is defined as the difference between LL and PL. Liquid limits and plastic limits do not directly provide figures that can be used in planning calculations. Obtained from the Atterberg boundary experiment si an outline of the properties of the soil in question. Soils with high liquid limits usually have poor engineering properties, namely low carrying capacity, high compressibility, and difficult to compact (Soedarmo & Punomo, 1993). Rochmawati et al., (2020) grainsize is the determination of the size of the grain contained in a soil sample in the laboratory. Permeability is the speed of water seeping into the soil pore space (Pratama et al., 2017). Grainsize affects soil permeability, poorly graded soils have higher porosity and permeability values than well graded soils where in well graded soils smaller soil grains fill the cavities between large soil grains. Permeability is a complex property controlled by the physical properties of the soil and the liquid that passes through the soil (Long & Boylan, 2021).

Artificial intelligence (AI) is defined as intelligence demonstrated by an artificial entity. Such systems are generally considered computers. Intelligence is created and incorporated into a machine (computer) in order to do work as humans can (Nasution, 2020).

Soft computing is defined as a collection of computational techniques in computer science, which seeks to study, model, and analyze a particular phenomenon in order ti exploit the tolerance fot inaccuracy, uncertainty, and partial truth to be solved easily, robustness, and low cost of completion. Soft computing deals with partial truth, complex problems (Ibrahim, 2016). In its development, soft computing can provide implementation solutions in solving problems that were previously very difficult to solve by conventional computing methods. Some of the methods contained in soft computing, namely fuzzy logic, artificial neural network, evolutionary computation, probabilistic reasoning, genetic algorithm (Sutojo et al., 2011). In this study, the authors use the method artificial neural network.

Artificial Neural Network (ANN) is a type of artificial intelligence for information processing that has been developed by imitating the biological network of the human brain and its structure and operation inspired by the study of the structure neurons and the internal functions of the human brain (Raei et al., 2021). The human brain has a neural network consistingof several neurons that have connections with one another (Setiawan et al., 2017).

3. Methods

The research methodology begins with the collection of soil physical properties and permeability data. There is no specific selection of data collection. The data collected is data that has been tested before. then a training process with ANN is carried out to find the best network performance for testing and simulation. The ANN simulation results will be tested for accuracy and error. The results of high accuracy and small error are the most influential physical property parameters. As a control, the results of the ANN, namely the correlation coefficient (R) will be compared with a sensitivity analysis using the coefficient of determination (R^2). If the sensitivity results are the same, then the next stage will be compared with the existing empirical equations to determine which one is more optimal.

The forcasting models carried out are then validated using a number of indicators. Commonly used indicators are the mean of the Root Mean Square Error (RMSE), Mean Abosulute Percentage Error (MAPE), Mean Absolute Error (MAE), Mean Absolute Deviation (MAD), Mean Square Error (MSE), tracking signal, and stability testing (Fernando et al., 2021).

The research method uses 3 prediction indicators, with the correlation coefficient (R) using the ANN tool, with accuracy testing and MAPE (Mean Absolute Percentage Error), and with the coefficient of determination (R^2). The R value obtained from the ANN results is the most sensitive physical property parameter. If the value of R is close to 1, it is categorized as the most sensitive parameter and very strong predictive ability, see in Table 1.

Table 1. Standard for R Value

R Value	Explanation
0.80 – 1.00	Excellent
0.60 – 0.79	Good
0.40 – 0.59	Medium
0.20 – 0.39	Poor
0.00 – 0.19	Very poor

Source: (Sugiyono, 2007)

Then the R value obtained from ANN will be taken as a prediction value for accuracy and error testing. Predicted values that are close to the test value (actual) will have high accuracy and small error. Tha MAPE value range can be seen in Table 2.

$$\text{Accuracy (\%)} = 100\% - \text{MAPE (\%)} \qquad (1)$$

$$\text{MAPE (\%)} = \frac{1}{n}\sum_{t=1}^{n}\frac{|y-y'|}{y} \text{ x } 100 \qquad (2)$$

Description:
y' = predicted value
y = test value
n = number of data

Table 2. MAPE Value Range

Range MAPE	Discribtion
>50%	Poor prediction ability
20% - 50%	Prediction ability feasibel
10% - 19.99%	Good predictive ability
<10%	Excellent prediction ability

Source: (Kusuma et al., 2021)

After that, to strengthen the research results, a sensitivity analysis was carried out based on the R^2. The criteria for the R^2 see in Table 3.

Table 3. Criteria for R^2

R^2	Explanation
80% - 100%	Excellent
60% - 79.99%	Good
40% - 59.99%	Medium
20% - 39.99%	Poor
0% - 19.99%	Very poor

Source: (Sugiyono, 2007)

3.1 Data Collection

Data is taken from research by Irawan et al. (2013) as much as 80 data. The data used are data on soil physical properties, namely LL, PL, PI, %sand, %fines, %silt, %clay, and also permeability. The soil was taken from various locations in Riau province, namely Duri, Balam, Dumai, Minas, Rantau Bais, Lindai, Libo, Bekasap, Petapahan, Kota Batak, and Tandun.

3.2 Equipment

The tools or software used in this research are Microsoft Word 2016, Microsoft Excel 2016, and MATLAB 2017b.

4. Results and Discussion

4.1 Sensitivity Analysis Based on R Value

The R value obtained from ANN will be tested with the MAPE indicator. The results see in Table 4.

Table 4. Ranking of Soil Properties Based R Value

Parameters	R Average
%Fines	0.9941875
%Sand	0.9923775
%Silt	0.9898575
%Clay	0.94655
Liquid Limit	0.87059
Plasticity Index	0.784485
Plastic Limit	0.736235

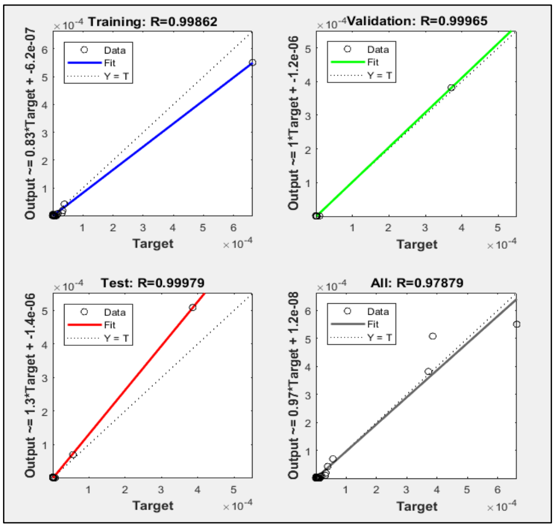

Fig. 1. ROC Curve with Physical Properties Parameters %Fines

Based on the sensitivity analysis based on the R value obtained from ANN, it can be seen that the most sensitive physical property parameter is %fines with an R value of 0.9941875. The following Receiver Operating Characteristic (ROC) curve of the %fines parameter can be seen in Figure 1.

Based on Figure 1, it can be seen that the training: R=0.99862, validation value: R=0.99965, test value: R=0.99979, and the value of all: R=0.97879. The R value in Table 4 is the average of the four R values in Figure 1. With the average R that has been obtained, it means that the ANN with the %fines parameter is very strong in making predictions.

4.2 Accuracy and Error Testing

The R value obtained from ANN will be tested with the MAPE indicator. The test results see in Table 5.

Table 5. MAPE and Accuracy Testing

Parameters	MAPE (%)	Accuracy (%)
%Fines	0.3038	99.6962
%Sand	0.3142	99.6858
%Silt	0.4212	99.5788
%Clay	0.8001	99.1999
Liquid Limit	0.9392	99.0608
Plastic Limit	1.0030	98.997
Plasticity Index	1.4605	98.5395

Based on accuracy and MAPE testing, it is found that %fines has a major influence on permeability values using ANN with an accuracy rate of 99.6962%. This means that the prediction ability using ANN is excellent, meaning that the permeability valued based on prediction is almost close to the permeability value based on testing.

4.3 Sensitivity Analysis Based On R^2

Sensitivity analysis based on the R^2 value by creating a linear curve with the abscissa of the soil physical properties parameter, the ordinate of permeability. The highest R^2 value will be categorized as the most sensitive or most influential physical property parameter.

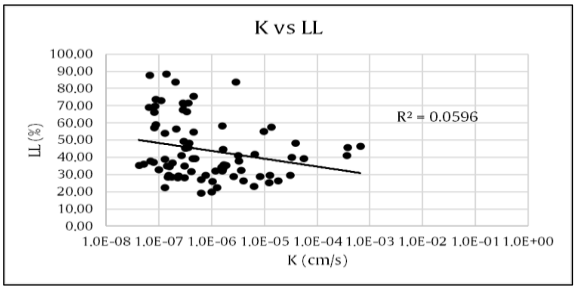

Fig. 2. Permeability Vs LL

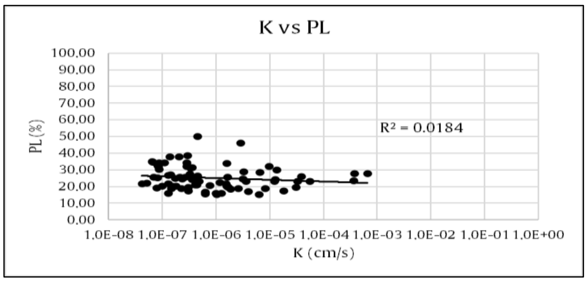

Fig. 3. Permeability Vs PL

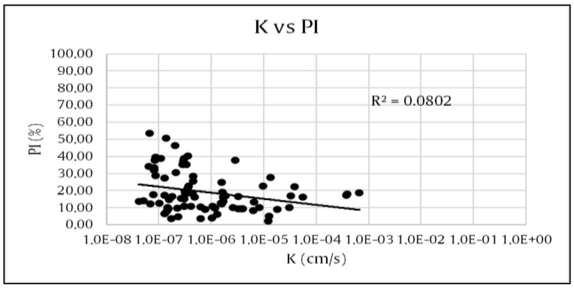

Fig. 4. Permeability Vs PI

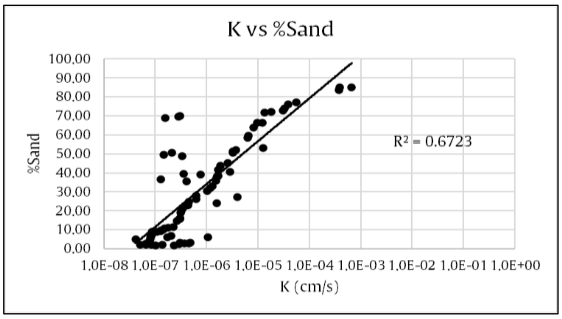

Fig. 5. Permeability Vs %Sand

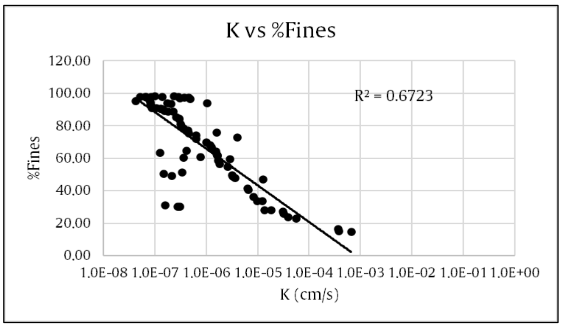

Fig. 6. Permeability Vs %Fines

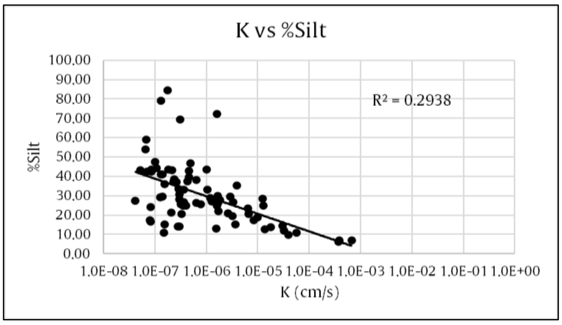

Fig. 7. Permeability Vs %Silt

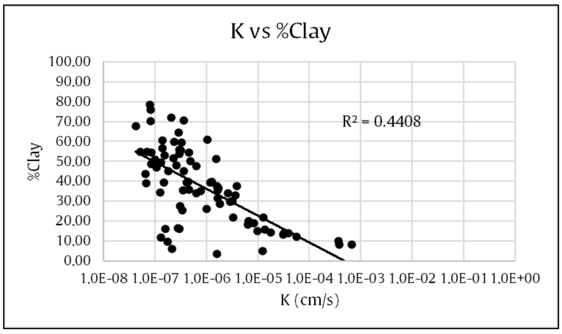

Fig. 8. % Clay Vs Permeability

Figure 2 to Figure 8 is a sensitivity analysis based on the R^2 of each soil physical properties parameter. The followong recapitulation of the R^2 see in Table 6.

Table 6. Ranking Based on R^2

Parameters	R^2
%Fines	0.6723
%Sand	0.6723
%Clay	0.4408
%Silt	0.2938
Plasticity Index	0.0802
Liquid Limit	0.0596
Plastic Limit	0.0184

Based on Table 6. It can be concluded that %fines has a strong correlation to permeability. This proves with the R indicator, accuracy and error testing, as well as with R^2, producing the same results, namely %fines which has great correlation. The following recapitulation of the three indicators see in Table 7

Table 7. Recapitulation of Prediction Indicators

Parameter	R
%Fines	0.9942
%Sand	0.9924
%Silt	0.9899
%Clay	0.9466
Liquid Limit	0.8706
Plasticity Index	0.7845
Plastic Limit	0.7362
Parameter	MAPE (%)
%Fines	0.3038
%Sand	0.3142
%Silt	0.4212
%Clay	0.8001
Liquid Limit	0.9392
Plastic Limit	1.0030
Plasticity Index	1.4605
Parameter	R^2

%Fines	0.6723
%Sand	0.6723
%Clay	0.4408
%Silt	0.2938
Plasticity Index	0.0802
Liquid Limit	0.0596
Plastic Limit	0.0184

4.4 Comparison of ANN Results with Empirical Equations

The prediction results generated by ANN using the %fines parameter will be compared to the empirical equation for calculating permeability using %fines data found by Irawan et al., (2013) research with the equation:

$$k = (205.209\ EXP\ (-0.081f))x\ 10^{-6} \quad \text{in cm/sec} \quad (3)$$

Description:
k = permeability coefficient (cm/sec)
f = percentage of fine grains (%)

The accuracy and error results of the ANN and empirical equation can be seen in Table 8.

Table 8. Comparison of ANN Accuracy and Error with Empirical Equation

Parameter	MAPE (ANN)	Accuracy	MAPE (Empirical Equation)	Accuracy
%Fines	0.3038%	99.6962%	3.5607%	96.4393%

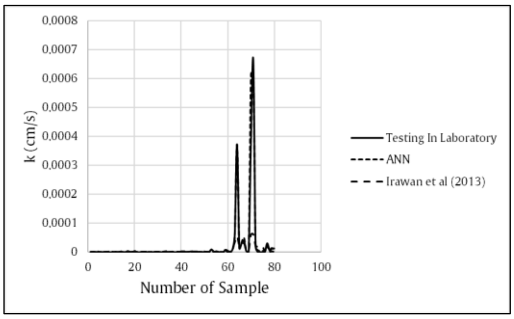

Fig. 9. Comparison of Permeability Values Based on Testing, ANN, and Empirical Equations

In Table 8, it can be seen that the prediction using ANN produces high accuracy and small error. In figure 9. It can also be seen the comparison of permeability curves between testing, ANN, and empirical equation, on the test curve and ANN, both are almost the same compared to the empirical equation. It can be concluded that ANN is more effective and optimal in predicting a value.

5. Conclusion

% Fines is the most influential physical property parameter on the permeability coefficient of cohesive soils, both using the correlation coefficient with the ANN tool and analysis based on the coefficient of determination (R^2). Both produce high values or close to 1 from other physical property parameters. The prediction ability using %fines is considered excellent in predicting compared to other soil physical properties parameters, which have accuracy values close to 100% and very small errors. After being compared with existing empirical equations, which have been found by (Irawan et al., 2013), ANN is more effective and optimal in predicting a value, seen from the comparison graph of permeability values and also from accuracy and error tests. The %fines data applies to the range of 14.82% to 98.36%, while the permeability data applies to the range of 4.1819E-08 to 6.6325E-04.

Acknowledgment

The authors wants to say thank you to Hendra Irawan, Soewignjo Agus Nugroho, and Syawal Satibi for allowing us to use laboratory testing data in the form of atterberg limit, grainsize, and permeability data.

References

Abiodun, O. I., Jantan, A., Omolara, A. E., Dada, K. V., Mohamed, N. A. E., & Arshad, H. (2018). State-Of-The-Art In Artificial Neural Network Applications: A Survey. *Heliyon*, *4*(11), e00938. https://doi.org/10.1016/j.heliyon.2018.e00938

Amanda, N. (2022). *Model Korelasi Empiris Sifat Fisik Dengan Permeabilitas Tanah Menggunakan Artificial Neural Network*.

Das, B. M. (1995). Mekanika Tanah (Prinsip-prinsip Rekayasa Geoteknis). In *Penerbit Erlangga*. Erlangga.

Fernando, H., Nugroho, S. A., Suryanita, R., & Kikumoto, M. (2021). Prediction of SPT Value Based on CPT Data and Soil Properties Using ANN With and Without Data Normalization. *International Journal of Artificial Intelligence Research*, *5*(2), 123–131. https://doi.org/10.29099/ijair.v5i2.208

Ibrahim, D. (2016). An Overview of Soft Computing. *Procedia Computer Science*, *102*(August), 34–38. https://doi.org/10.1016/j.procs.2016.09.366

Irawan, H., Nugroho, S. A., & Satibi, S. (2013). *Korelasi Permeabilitas Berdasarkan Ukuran Butiran dan Plastisitas Tanah. 1989*.

Kusuma, S., Suhery, C., & Hidayati, R. (2021). Implementasi Metode Weighted Moving Average Pada Sistem Prediksi Stok Tembakau Lokal Berbasis Web (Studi Kasus Outlet Progressive Nicotiana). *Coding Jurnal Komputer Dan Aplikasi*, *9*(3), 400–410.

Long, M., & Boylan, N. (2021). In-Situ Testing of Peat - a Review and Update on Recent Developments. *Geotechnical Engineering Journal of the SEAGS & AGSSEA*, *43*(4).

Maharani, P. H., Sunarminto, B. H., & Hanudin, E. (2015). *Penggunaan Fungsi Pedotransfer untuk Memperkirakan Permeabilitas Tanah di Sumatera Selatan dan Riau*. *18*(1), 37–43.

Naim, Priadi, E., & Aprianto. (2019). Pemetaan Zonasi Geoteknik Di Kota Pontianak Berdasarkan Data Konsistensi dan Sifat-Sifat Tanah Dengan Sistem Informasi Geografis. *Jurnal Agroekoteknologi Tropikapertanian*, *24(1)*(21), 16.

Nasution, H. (2020). Implementasi Logika Fuzzy pada Sistem Kecerdasan Buatan. *ELKHA: Jurnal Teknik Elektro*, *4*(2), 4–8. https://jurnal.untan.ac.id/index.php/Elkha/article/view/512%0Ahttp://download.garuda.kemdikbud.go.id/article.php?article=1559615&val=2337&title=Implementasi Logika Fuzzy pada Sistem Kecerdasan Buatan

Padagi, E. A., Priadi, E., & Aprianto. (2015). Korelasi Nilai N-SPT Terhadap Sifat Fisik dan Mekanis Tanah. *Jurnal Mahasiswa Teknik Sipil Universitas Tanjungpura*, *1*(1), 1–11. https://jurnal.untan.ac.id/index.php/JMHMS/article/view/10244

Pratama, I. M. R., Yulianti, I., & Masturi, M. (2017). Analisis Sebaran Butiran Agregat Tanah, Sebaran Butir Primer Tanah, dan Permeabilitas Tanah Pada Pabrik Teh. *JIPF (Jurnal Ilmu Pendidikan Fisika)*, *2*(1), 7. https://doi.org/10.26737/jipf.v2i1.196

Raei, B., Ahmadi, A., Neyshaburi, M. R., Ghorbani, M. A., & Asadzadeh, F. (2021). Comparative Evaluation Of The Whale Optimization Algorithm And Backpropagation For Training Neural Networks To Model Soil Wind Erodibility. *Arabian Journal of Geosciences*, *14*(1). https://doi.org/10.1007/s12517-020-06328-0

Rochmawati, R., Irianto, & Lau, L. M. (2020). Studi Eksperimental Penentuan Jenis Tanah Berdasarkan Distribusi Ukuran Butiran Tanah. *Journal of Portal Civil Engineering*, *3*(2), 145–154.

Setiawan, B., Suryanita, R., & Djauhari, Z. (2017). Prediksi Tingkat Kinerja Struktur Gedung Kantor Berdasarkan Mutu Beton Dengan Metode Jaringan Saraf Tiruan. *SIKLUS: Jurnal Teknik Sipil*, *3*(2), 107–116. https://doi.org/10.31849/siklus.v3i2.393

Soedarmo, G. D., & Punomo, S. J. E. (1993). *Mekanika Tanah 1* (Vol. 15, Issue 2, pp. 1–23). KANISIUS.

Sugiyono. (2007). *Metode Penelitian Kuantitatif Kualitatif dan R&D*. Alfabeta.

Sutojo, T., Mulyanto, E., & Suhartono, V. (2011). *Kecerdasan Buatan*. ANDI.

Yantrapalli, S. K., P, H. K., & K, S. (2018). A Study On Influence Of Real Municipal Solid Waste Leachate On Properties Of Soils In Warangal, India. *Journal of Geoscience, Engineering, Environment, and Technology*, *3*(1), 25. https://doi.org/10.24273/jgeet.2018.3.1.1047