A review of applications of artificial intelligence in geotechnical engineering.

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ABSTRACT: Artificial intelligence (AI) has emerged as a transformational enabler in the geotechnical field, offering innovative solutions to solve complex challenges. This research endeavor offers a literature review delving into the utilization of diverse artificial intelligence techniques, notably machine learning and Artificial Neural Networks, for the estimation of soil parameters and the prediction of various geotechnical phenomena. This aids engineers, researchers in AI evolution in geotechnics.

1 INTRODUCTION

Artificial intelligence (AI) is an evolving field with many practical applications and active research topics. It aims to develop computer systems capable of solving problems that require human intelligence, such as decision-making, speech recognition, shape and texture recognition, etc. Currently, AI is used in many fields, such as medicine, finance, national security and research, etc. (AOUADJ, 2023)

Among these fields' geotechnics, with the aim of developing the field of geotechnical engineering several studies have been done to facilitate and predict certain parameters.

This review embarks on an exploration of the applications of AI in geotechnics, delving into the multifaceted ways in which intelligent algorithms and machine learning techniques are enhancing our understanding, analysis, and management of geological and geotechnical challenges. From foundation design to soil classification, estimation of cohesion and compaction parameters, the incorporation of AI technologies holds the promise of not only improving efficiency and accuracy but also uncovering novel insights and solutions.

2 LITERATURE REVIEW FOR MACHINE LEARNING

2.1 *Geotechnical data using in AI*

Big data offers a powerful platform to assemble and analyze transportation infrastructure data that can be utilized to predict asset behaviour. Both structured and unstructured forms of data including the historical datasets with respect to site location, weather conditions, traffic, soil type, pavement condition, sensor data, and other factors influencing the performance of the assets are typical in geotechnical practice. (Amit G., 2022).

- Sensor data: Sensor data can be used to measure geotechnical parameters such as forces, displacements, pressure, temperature, humidity, water level, etc. Sensors can be installed in the ground or on structures to measure these parameters.
- Geological data: Geological data, such as borehole data, geological mapping data and aerial images taken by drones and inspection cameras as well as tiltmeter and remote sensing data, can be used to characterize properties geological aspects of the soil and rock as well as the geometry of the sites.

- Test data: Laboratory test data, such as the results of triaxial tests, box shear tests, oedometer tests, or the results of in situ tests using a pressuremeter, static, dynamic or SPT penetrometer, permeability tests, etc., can be used to characterize the mechanical and hydraulic properties of soil and rock.
- Climate data: Climate data, such as weather data and climate change data, can be used to predict the effects of climate on infrastructure and land stability. (AOUADJ, 2023)

2.2 *Machine learning*

Machine learning is a sub-discipline of artificial intelligence that focuses on developing algorithms and models that enable computers to learn from data and improve their performance on a specific task. It also encompasses many methods such as artificial neural networks (ANN), decision tree techniques, support vector machines (SVM), evolutionary algorithms (EA) such as genetic algorithms and genetic programs.
Figure 1 presents a simplified classification of AI methods. (Goodfellow, 2016)

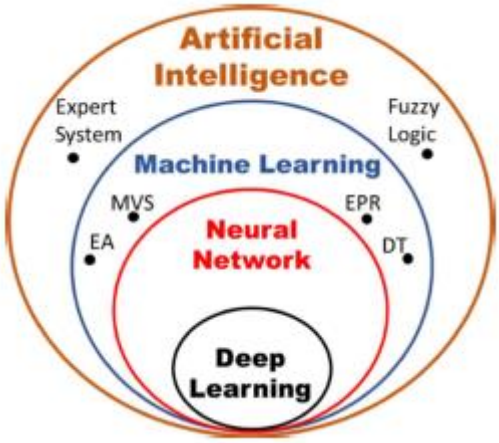

Figure 1:Classification of AI methods.

2.3 *Neural network*

A neural network can be considered as a mathematical model of distributed processing, composed of several non-linear computational elements (neurons), operating in parallel and connected together by weights. Artificial neural networks (ANN) are highly connected networks of elementary processors operating in parallel. Each elementary processor calculates a unique output based on the information it receives. (Ammar, 2007)
A neural network is a network that processes input data by connecting many modeled neurons, these formal neurons are connected in layers. In a hierarchical neural network, the initial layer, known as the input layer, tasked with receiving the initial data information. The last layer of the network is designated as the output layer, responsible for presenting the final calculation results. Positioned between the input and output layers, the intermediate layer, also known as the hidden layer, receives output from the preceding layer, performs calculations, and forwards the results to the subsequent layer. The structure of this middle layer in the neural network exhibits a high degree of freedom, allowing for versatile operations in alignment with the intended purpose.
The consequence of this joined summation is achieved through a transfer function that can also be utilized depending upon the type of problem to be solved by the network (e.g. linear; sigmoidal; Tangent sigmoidal function). this procedure is shown in Equations 1 and 2 and illustrated in Figure 2. (Benbouras M. A., 2018)

$$I_j = \sum W_{ji}\, Xi + \theta_i \qquad 1$$

$$Yi = f(Ii) \qquad 2$$

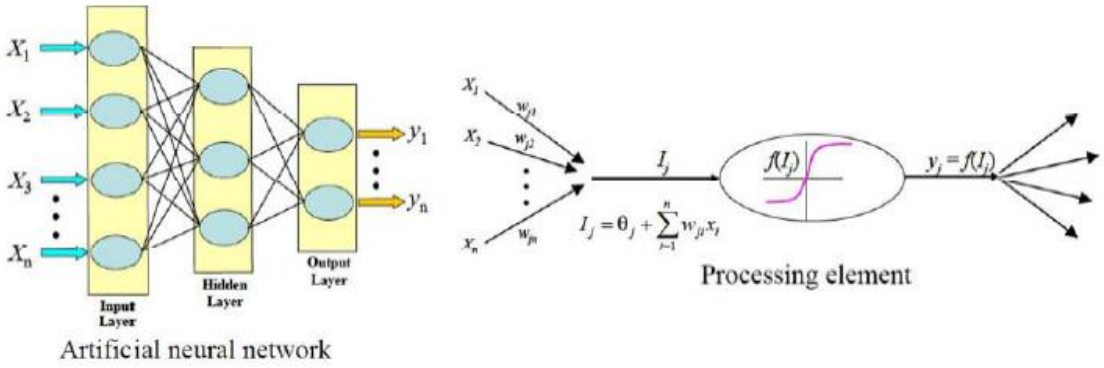

***Figure 3**: A model structure and modus operandi of Artificial Neural Networks (Shahin M. A., State of the art of artificial neural networks in geotechnical engineering , 2008)*

According to equations, we can define the formal neuron as follows: A "formal neuron" (or simply "neuron") is a nonlinear and bounded algebraic function, the value of which depends on parameters called coefficients or weights. The variables of this function are usually called the "inputs" of the neuron, and the value of the function is called its "output" (AOUADJ, 2023).
A fundamental methodology of ANN is composed of three stages, Network training, Network testing and Network validation." Training" the neural network involves modifying the connected weights by providing repeatedly a historical range of model inputs and corresponding desired outputs. The aim is to reduce errors between the expected and desired output values. And continue the training process using Back Propagation Algorithm in order to achieve some stopping criteria so that the network could get a bundle of weights and bias unit that will produce the smallest possible error (Benbouras M. A., 2018).
it is essential to check that the model performs consistently on all three data sets (i.e. training, testing and validation). The coefficient of correlation, r, the root mean square error, RMSE, and the mean absolute error, MAE, are the major criteria that are used to evaluate the performance of the model. Smith suggested the following guide for values of |r| between 0.0 and 1.0 (Shahin M. A., 2000):

- $|r| \geq 0.8$ Strong correlation exists between two sets of variables.
- $0.2 < |r| < 0.8$ Correlation exists between the two sets of variables.
- $|r| \leq 0.2$ Weak correlation exists between the two sets of variables.

2.4 *Deep learning*

Deep learning is a subfield of machine learning that involves the use of neural networks with multiple layers (deep neural networks) to learn and make intelligent decisions.
Deep learning is making major advances in solving problems that have resisted the best attempts of the artificial intelligence community for many years. It has turned out to be very good at discovering intricate structures in high-dimensional data and is therefore applicable to many domains of science, business and government. In addition to beating records in image recognition and speech recognition, it has beaten other machine-learning techniques at predicting the activity of potential drug molecules, analysing particle accelerator data, reconstructing brain circuits, and predicting the effects of mutations in non-coding DNA on gene expression and disease. (LeCun, 2015)

3 APPLICATIONS OF ARTIFICIAL INTELLIGENCE IN GEOTECHNICAL ENGINEERING

In order to enhance the analysis of information and results in the field of geotechnical engineering and its disciplines, including soil classification, foundation calculations, and even the prediction of soil mechanical properties, artificial intelligence and machine learning techniques have been introduced. This literature review aims to highlight some of these research findings and previous studies.

3.1 *Soil classification*

(Shinya I, Sutasinee I, Apiniti J, Susit C & Kazuhiko K). (Shinya, 2020), they developed an artificial intelligence-based model, more precisely using the artificial neural network (ANN) technique, for soil classification. Thus, the soil to be classified was divided into three types (clay: D50=0.008 mm, sand: D50=0.7 mm and gravel: D50=4 mm), where the particle size was adjusted using a sieving test, and the water content set to 0 for simplicity. The samples were arranged in transparent cups to capture images using a smartphone (iPhone 7) and a digital camera (Fujifilm XT4). It should be noted that the two cameras differ in terms of pixels and sensors, which influences the quality of the images.
Table 1 presents a list of prepared images. These 1000 images were used as the learning data, and a total of 60 images of each randomly selected 20 images were used as model accuracy verification data. (Shinya, 2020)

Table 1:Types and numbers of images taken. (Shinya, 2020)

	Clay	*Sand*	*Gravel*	*(Total)*
Presence of lighting	200	200	100	500
Absence of lighting	200	200	100	500
(Total)	400	400	200	1000

The batch size represents the number of learning images divided into groups and used in one learning session. In consideration of the balance between the required time and the number of trials, the batch size was set to 20 in this study. (Shinya, 2020)

In the end this AI model was able to recognize and classify the soil with an accuracy of 86% in total, and the highest percentage is that of sand with an accuracy of 100%.

3.2 *Estimation of cohesion (Cu)*

In order to minimize the cost and time of the shear test, which aims to evaluate the mechanical characteristics of soils or rocks, an optimization study carried out by (BENBOURAS and al) (BENBOURAS, 2018). This study proposes a new approach to estimate the cohesion (Cu) in 5 types of soils clay, sand, marl, silt and gravel. The experiments were conducted on 533 samples were obtained from 73 core drillings, the depth of which varies between 10 and 103 m with an average of 49.6 m. The data was collected from a number of projects in Algiers carried out by different geotechnical laboratories.
To identify the appropriate model for the estimation of Cu, first they created a geotechnical database on the soil studied, including several variables such as: water content, Atterberg limits, wet density, particle size analysis by sieving and shear strength. Afterwards, these data were analysed by two methods in order to find the most suitable model, the first is the application of some multiple regression analysis models and the second by an artificial neural network (ANN) model, where six parameters were used in the input layer. (wet density (ρh), plasticity index (PI), water content (w), liquid limit (LL), fine particles and soil type). Five soil types were considered (clay = 1, marl = 2, silt = 3, sand = 4 and gravel = 5).

The most appropriate ANN model proposed by this study guarantees better predictability in data learning and gives data prediction values close to those of the experimental ones. (BENBOURAS, 2018)

3.3 *Soil compaction parameters*

soil compaction is defined as the process of pressing the soil particles together by decreasing pores, space and preserving the water content between them. (Verma, 2020)
In order to determine the optimal model for predicting the compaction parameters, an international database consisting of 147 samples was collected. The step was performed with the assistance of Proctor and soil identification tests. Then, the inputs were modeled by means of a number of machine learning methods, which are as follows: ELM, DNN, SVR, RF, LASSO, PLS, Ridge, K Ridge, Stepwise, and PG. The third step is to detect the optimal model for estimating the compaction parameters, by comparing between the proposed ML models. Finally, The K-cross-validation approach (with k = 5) was utilized for the sake of evaluating the predictive capability of the optimal model in overcoming under-fitting and over-fitting problems, and the finalized optimal model was used to create a reliable graphic and easy-to-use interface dubbed "ComPara2021". (Benbouras, 2021). Figure 3 illustrates the methodology that was followed to define the optimal model.

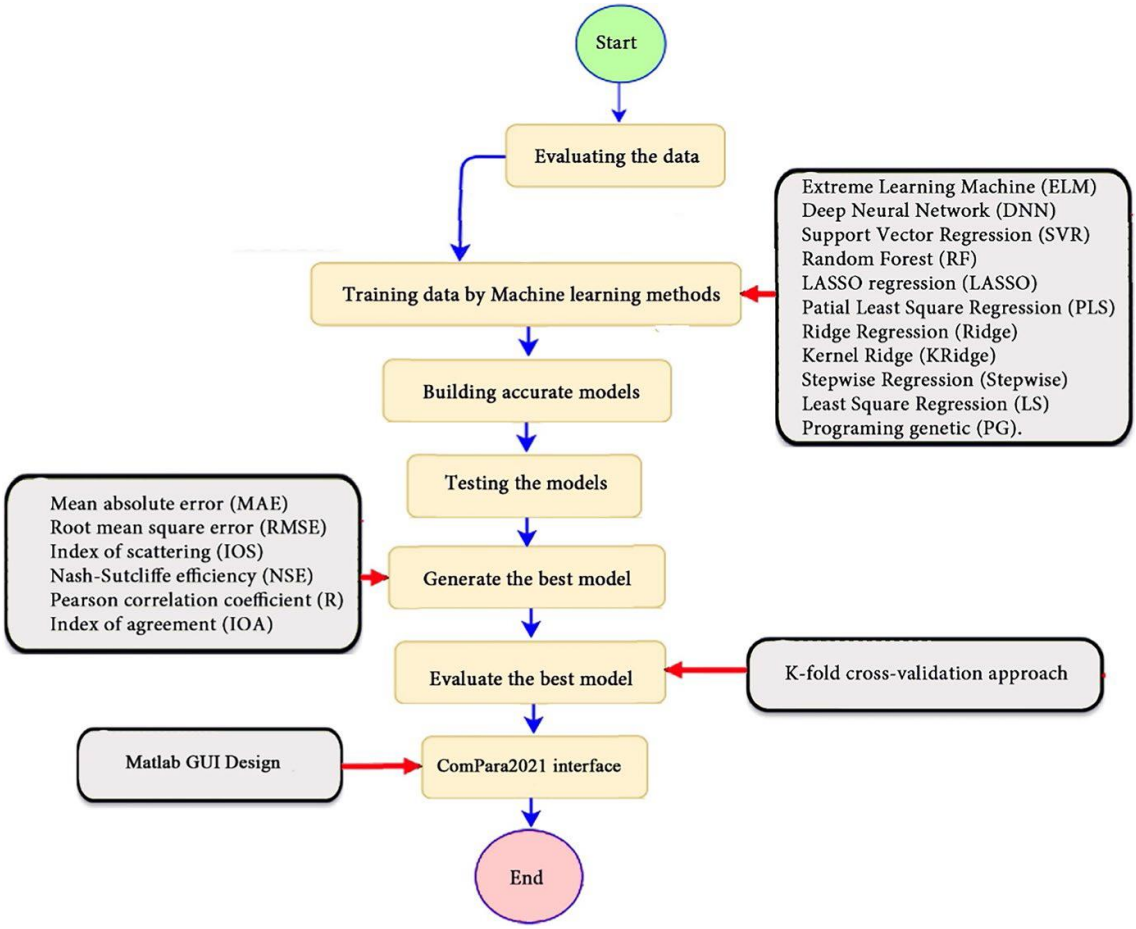

Figure 4: Flowchart describing the key steps for the methodology of research to estimate compaction. (Benbouras, 2021)

The results indicated that the suggested RF (random forest) model is much more effective than the other empirical models and it revealed its superiority also compared to the other models proposed.

3.4 *California bearing ratio (CBR) Index*

The CBR index is a very important parameter in road geotechnics, it allows us to know the ability to use a specific soil in embankments or subgrade layers, this parameter is determined by laboratory tests and this requires a qualified technician as well as significant time.
This work intends to propose a prediction model index after immersion based on a neural approach using an enhanced Database of geotechnical parameters easily measurable [VIJ 13]. To ensure the reliability of the chosen prediction model, the authors conducted three parallel studies: Simple regression, multiple regressions, and of artificial neural network. (BOUROUIS, 2015)
At the end this study shows that the ANN model is more efficient than the multiple regression model, and it is necessary to use a large number of parameters to give reliable prediction accuracy. Figure 4 shows the comparison between the multiple regression analysis and the artificial neural network.

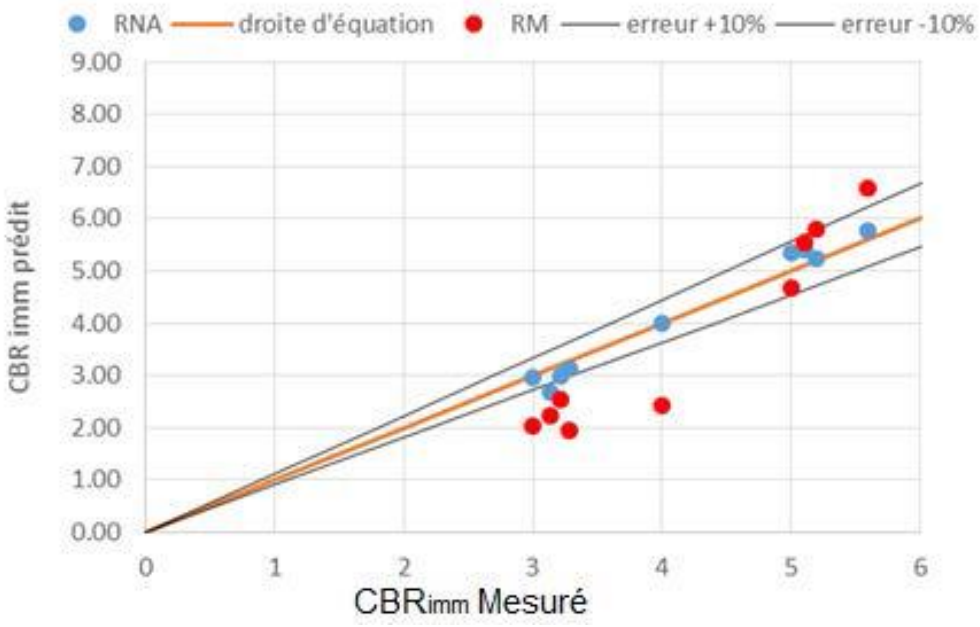

Figure 5: Comparison between multiple regression analysis and artificial neural network. (BOUROUIS, 2015)

3.5 *Foundation engineering*

Foundation in geotechnical engineering refers to the substructure or support system that transfers loads from a structure to the underlying soil or rock, providing stability and preventing settlement. It serves as the interface between the superstructure and the ground, distributing loads effectively to ensure the overall structural integrity of a building or infrastructure. (Terzaghi, 1996)

Sivakugan and al. (1998) (Shahin, 2001) explored the possibility of using neural networks to predict the settlement of surface foundations in grainy soils. An ANN was formed with five inputs representing applied net stress, mean number of core penetration test (Nspt) hits, foundation width, foundation shape, and foundation depth. The network output was the settlement of the foundation. The model was developed using 79 shallow foundation loading tests. 69 cases for training the model and 10 cases for testing its performance. The results are encouraging. (AOUADJ, 2023)

Were other studies on deep foundations to predict the behaviour of piles subjected to vertical and lateral loading.

Goh (1995) (Goh, 1995) developed an ANN model to predict the lateral friction resistance of piles in clayey soils.

The inputs are: pile length, pile diameter, average effective stress and undrained shear strength. Side friction resistance is the only output of the model. the results were compared by traditional methods like that of Semple and Rigden (Semple, 1986), and that of β (Burland, 1973), and the ANN model outperformed these methods.

The use of a hybrid modelling system with mathematical models makes it possible to overcome some of the disadvantages of AI. It offers better transparency compared to black box modelling, and better prediction accuracy. Mathematical models often have high accuracy, but they may not account for certain variables that may impact the final result. AI can be used to improve forecast accuracy by including additional variables or detecting nonlinear relationships between variables. (AOUADJ, 2023)

4 CONCLUSION

It was 35 years ago since the first usage of Artificial Intelligence (AI) technique in geotechnical engineering, during those years many (AI) techniques were developed based in mathematical, statistical and logical concepts (Ebid, 2021). Artificial intelligence and machine learning have proven their effectiveness in the geotechnical field, and this review has confirmed that, hence the use of this technology reduces us more time and cost. On the other hand, there were also disadvantages which were observed when using AI in geotechnics for example:

- the need for a large quantity of database for more reliable predictions.
- sometimes the prediction results do not exactly simulate the real results.

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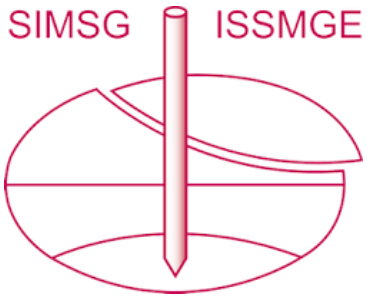

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The paper was published in the proceedings of the 18th African Regional Conference on Soil Mechanics and Geotechnical Engineering and was edited by Abdelmalek Bekkouche. The conference was held from October 6th to October 9th 2024 in Algiers, Algeria.