Applications of Artificial Intelligence and Machine Learning in Geotechnical Engineering

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Abstract— *The primary objective of this paper is to examine the many ways in which Artificial Intelligence (AI) and Machine Learning (ML) may be used in the field of Geotechnical Engineering. Researchers in the geotechnical engineering sector have been developing and using artificial intelligence (AI) and machine learning (ML) approaches for the last three decades. As a result of their efficacy in predicting complicated nonlinear interactions [1], these techniques have been widely used. Machine learning (ML) has recently piqued geotechnical engineers' attention due to its widespread usage in a variety of fields. Past reviewed studies have generally focused on machine learning methods; however, this work promotes an agenda that puts data at the center, develops unique techniques that are appropriate for geotechnical data (current and emerging), addresses the demands of present practice, exploits new possibilities from technological breakthroughs or meets emerging needs from information technology and takes use of existing knowledge and collected experience [1]. The three main components of this agenda—data centricity, fit for (and transformation of) practices, and geotechnical context—are together referred to as data-centric geotechnics. This "data first, experience core" goal will guide future geotechnical machine learning.*

Keywords: Soil Properties, Liquefication, Machine Learning, Artificial intelligence, Artificial Neural Network (ANN)

I. INTRODUCTION

Computers may learn from existing data without being explicitly programmed thanks to machine learning (ML), a branch of Artificial Intelligence (AI). Recently, the use of machine learning across a broad variety of sectors has increased significantly. Big data may now be subjected to sophisticated analyses like machine learning (ML) thanks to advances in computer computational power over the last several decades [1]. Recent success stories in geotechnical engineering using AI and machine learning give enough incentive to revisit and debate previously published work in this area. AI and machine learning-based approaches in geotechnical engineering are examined, along with the variables that influence their use, in this research. Geotechnical engineering review articles from the past[1,2] have all concentrated on a single topic. Ground-based materials like soil and rock are studied in geotechnical engineering (e.g., coal). A broad number of engineering fields rely on it, including pavement structures and foundations, canals, landfills, seismic events, groundwater mineral prospecting, and underground mining slop stabilization.

Geotechnical engineering is especially suited to the use of artificial intelligence because of the variability of soils and the uncertainties involved with sampling, testing, and modeling. During this discussion, an introduction to the many approaches of artificial intelligence will be given. Particular attention will be paid to machine learning techniques, algorithms, and how these methods may be used to a variety of geotechnical engineering issues. The discussion will give an overview of various methods and examine the advantages and disadvantages of using them. In addition, a number of case models will be given to demonstrate AI's versatility and power [2].

II. RESEARCH PROBLEM

The main problem that will be solved by this paper is to analyze the applications of Artificial Intelligence and Machine Learning in Geotechnical Engineering. All geotechnical engineering constructions begin with a thorough analysis and categorization of the subsoil's qualities. Today, geotechnical design relies heavily on rock mass categorization techniques. Classifications that are based on subjective or semi-quantitative evaluations, on the other hand, are increasingly in demand [3]. Performing the required soil testing and lab analysis may be expensive and time consuming. Different supervised machine learning models are used in the newest work to analyze subsurface conditions. Machine learning (ML) and other sophisticated analytics have become possible because to the rise in machine processing power over the last several decades. With the inherent uncertainty in geotechnical engineering, machine learning (ML) may be an efficient tool for developing reliable predictive models of various soil and foundation engineering characteristics. Rather of relying on direct measurements from lab and in-situ testing, geotechnical design parameters are frequently calculated using correlations derived through regression fitting of a dataset. Artificial Neural Networks (ANNs) may considerably enhance these empirical correlations by using multi-dimensional nonlinear modeling approaches such as linear regression methods (ANNs).

III. LITERATURE REVIEW

A. Machine learning and artificial intelligence in geotechnical engineering

Soil and rocks are responsible for the majority of what we see and touch every day. A subspecialty of civil engineering, geotechnical engineering studies the characteristics and behavior of earth materials (soil, rock, and their derivatives) in the context of investigating, building, and designing different civil engineering structures. Soil and rock, the two primary geotechnical engineering materials, exhibit a broad range of behavior and properties [4]. In addition to the homogeneity and isotropy of their fundamental structure, these materials' diversity is related to a broad range of intricate and unpredictable changes that are responsible for their manifestation. Steel, bricks, stones, lime, and asphalt are common engineering and construction materials that exhibit a greater degree of homogeneity and isotropy.

This makes it easy to predict their behaviors and model them. In the design and serviceability analyses of geotechnical materials, this undeterminable and unexpected behavior makes it difficult. Furthermore, certain complicated engineering issues lack analytical theories, empirical equations, or models that may otherwise provide a solution [4][5]. As a result of lack of knowledge, poor quality, and limited number of accessible information, many conventional techniques are ineffective. Computer-based modeling tools are increasingly being used to address the intricacy of these design solutions, which are beyond the capabilities of conventional methodologies. In mathematics, a computer-aided method to physics and mechanics is used to simulate, analyse, and imagine the system's performance and behaviour. The "Artificial Intelligence (AI)" approach has gained a lot of traction in recent years as a fresh and innovative solution for solving geotechnical engineering design problems [4,5]. Soil behavior may be predicted using artificial intelligence (AI) by developing algorithms based on existing empirical data. Unlike most conventional statistical and empirical approaches based on physical properties, AI techniques may be used even when the physical meaning or underlying connections between variables are unclear. AI systems are able to anticipate future behaviors, structures, and patterns if they are given a sample of data that is similar to the data they are trying to forecast. This means that rather than relying on fundamental assumptions, AI systems develop outputs based on maps constructed by them using just the inputs they receive [5]. It is not necessary for AI systems to understand basic assumptions and connections between the data they receive as input. As long as they have enough information, they can figure it out for themselves. An AI system gathers data from a variety of sources and generates model outputs. Until a function is developed that minimizes the discrepancy between AI model predictions and actual outputs, these model outputs are created. In contrast to regression models, which can only deal with a single answer at a time, AI approaches have gained in favor because of their great predictive potential and their capacity to deal with several replies at once (Park, 2011). Non-linear regression data may be used in AI models without any previous awareness of the existing non-linearity in the datasets itself. Non-linear statistical regression data may only be analyzed if the nature of the non-linearity is understood. To describe complicated mechanical behavior, neural networks (NNs) include universal functions, such as resistance to missing data, generalization, approximation, and the capacity to accommodate many nonlinear variables for unknown interactions. This is why artificial intelligence (AI) approaches are a superb alternative not just to traditional ways, but they are also vital in circumstances when conventional methods are unable or unable to handle the situation.

B. Geotechnical engineering may benefit from artificial intelligence.

The term "artificial intelligence" (AI) refers to the intelligence shown by computers and other electronic devices. Machines taking control of our life or even "ruling the planet" used to be a worrisome concept for many people. True, AI is transforming our world, but no one is complaining. When they ask their "smart" phones for directions or directions to a coffee shop, many individuals today are already using AI in their daily lives. However, it wasn't until the early 2000s that developments in artificial intelligence (AI) were widely accepted. It is possible to use AI in a variety of industries. When it comes to computer science, artificial intelligence (AI) learns from its surroundings and performs actions that will help it achieve a certain objective (s). Geological engineering prediction relies mostly on experience and understanding automated systems and neural network technologies to find solutions to challenges. Predictions of long-term performance of pavements, as well as assessments of rock fall or slope stability may all be made using AI systems [7]

In many transportation situations, rock slope instability may lead to hazardous circumstances, as well as financial and functional losses. For both public and private usage, it is critical to map the possibility for rock slope collapse. Artificial Intelligence (AI) technologies may be used to quickly and cost-effectively create slope failure potential maps.

Professional experts' expertise and the ambiguity of their assessments may first be used to estimate the likelihood for breakdown of gradients. GIS datasets are utilized as a framework for artificial intelligence (AI) assessment in order to predict slope instability [8]. Geological and topographic data are entered into a database in GIS to get the process started. Slope failure potential maps are then generated by the AI system utilizing the known connection between the model variables in order to represent the complicated situation. The maps of slope failure potential created using AI systems also help with slope maintenance by prioritizing follow-up operations to reduce the issue, such as leading more extensive studies and deciding effective techniques to monitoring and establishing an early-warning system.

So, the geotechnical engineering profession is benefiting greatly from AI. Is it on its way to conquering the globe? No chance! However, geotechnical engineering stands to benefit greatly from AI. We will need more engineers to investigate, design, and test AI systems as a result of AI advancements[9]. Taking part in the development of AI is a terrific chance for the technical community to show off our inventiveness while helping to shape its long-term efficacy.

C. Application of Geotechnical Machine Learning Techniques

In geotechnical engineering, where there is a great deal of uncertainty, machine learning (ML) may be an efficient tool for developing predictive models of soil and foundation engineering characteristics and behaviors. Rather of relying on direct measurements from lab and in-situ testing, geotechnical design parameters are frequently calculated using correlations derived through regression fitting of a dataset. Artificial Neural Networks (ANNs), a multi-dimensional nonlinear modeling methodology, may considerably enhance these empirical correlations, which typically employ linear regression methods [10]. ANNs may be used to predict the undrained shear strength of clay, and this article provides a review of previous works on the use of ML in geotechnics. A local dataset was used to create and train ANN models. Predicting undrained shear strength using ANN models was evaluated. The anticipated and observed undrained shear strength values were compared, and it was found that the predictions were quite accurate.

D. Artificial Neural Network (ANN)

In geotechnical engineering, (ANN) is one of the most often utilized AI approaches where modeling of complicated engineering challenges where the interaction between the model and the problem may be simulated. It is possible to store and analyze data from a variety of sources using ANN externally provided information. ANNs are taught by seeing successful examples in the real world. Many basic, densely linked nodes make up the Artificial Neural Networks (ANNs) neurons grouped in input, output, and hidden levels of processing. In light of the above, Weighted links connect the ordered levels. Each neuron is connected to every other neuron in the body. next layer of neurons. The input layer is where the network gets its patterns. An interaction between the input layer and there are even more strata to uncover. A connection is created in the hidden levels where the actual processing takes place weighted connections are used to link the inputs and outputs.

The Artificial Neural Network, often known as ANN, is one of the AI approaches that is used the most frequently in geotechnical engineering. It is considered to be a potentially useful tool in the modeling of complicated engineering issues, particularly those in which the connection between the model variables is unclear or where physical visualization is impossible. An ANN is a distributed processor that can store and process information from a data set that originates outside of the network. Training patterns and examples of input-output relations are presented to the ANN, which learns from them.

i. Structure of ANN

The input, output, and hidden layers of an ANN's structure consist of a large number of basic but densely linked processing units (PEs) known as neurons. Weighted links connect these logically arranged levels. There is a direct connection between each neuron and every other neuron in the following layer. The input layer is where the network gets its patterns. There may be more than one hidden layer that is involved in the input process. An arrangement of weighted connections establishes the interaction between inputs and outputs in the hidden layers where actual processing takes place.

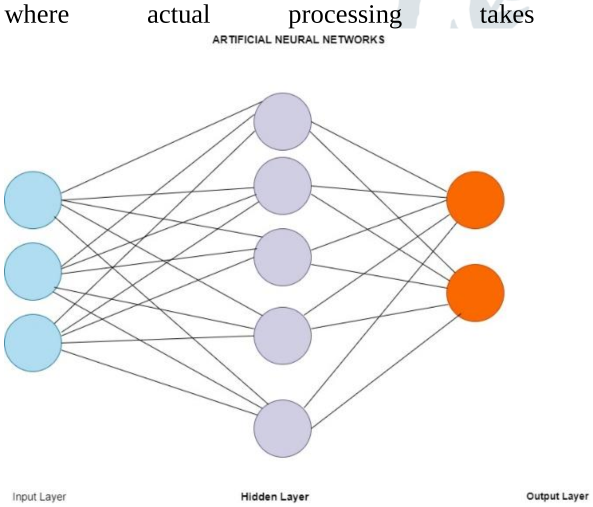

Fig i: ANN structure

ii. Geotechnical engineering uses for ANN

1. Settlement of foundations

Predicting settling is essential when planning any foundation. Geotechnical engineers have long regarded foundation settlement to be a difficult phenomenon to fully understand because of the complexities and unpredictability of its behavior. Researchers used ANNs to estimate the settling of pile foundations and shallow foundations in homogeneous, granular, and cohesionless soils because of this characteristic. To anticipate the settling of piling foundations, an artificial neural network was used. Predicting settling of deep foundations on granular soils [11] is possible with an ANN. An artificial neural network (ANN) was trained on the foundation's form, depth and breadth, penetration test blow count, and net pressure. In this instance, the predicted outcome was likewise a settlement of the foundation. For cohesionless soils, ANNs were also used to predict the settling of shallow foundations. The ANN model used input variables such as applied pressure, footing length and breadth, and soil compressibility [11] as inputs. Again, foundation settlement was the predicted result. With its low root mean squared errors (RMSE), mean absolute errors (MAE), and high coefficients of correlation r, the ANN model outperformed the older techniques.

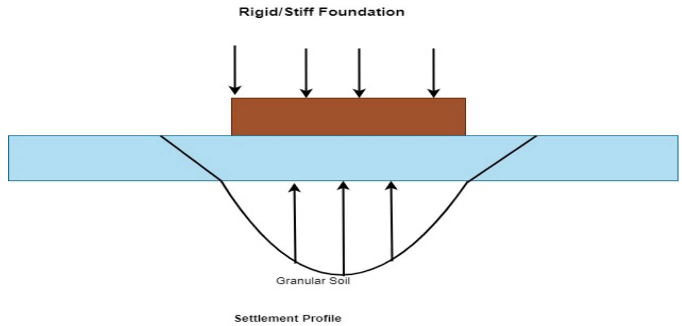

Fig ii: Illustration of settlement foundations

2. Liquefaction

As a consequence of abrupt pressure changes, such as during an earthquake, a saturated or partly saturated soil loses a significant amount of its shear strength. We're talking about liquefaction here. Civil engineering structures are at risk from liquefaction, making the evaluation of liquefaction potential critical. Due to its somewhat specified behavior features, however, it is a more complicated and time-consuming operation. The intricate link between soil parameters and seismic loads may be established using artificial neural networks (ANNs)[12]. Traditional approaches were then compared to the outcomes of the experiment. The technique had a success rate of 84%, whereas the ANN had a success rate of 95%.

3. Slope stability

The assessment of the stability of slopes is an extremely important part of engineering analysis. The possibility for failure on a slope may be predicted using Artificial Neural Networks in conjunction with fuzzy set theory. Analytical findings and neural network findings agreed [12].

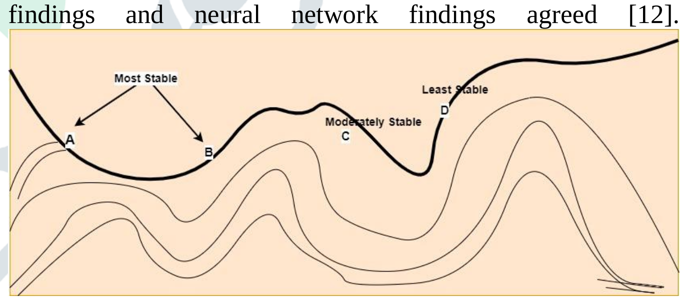

Fig iii: Illustration of slope stabilities

4. Soil properties

This technology has also been used in the prediction of soil qualities and characteristics. Back-propagation neural networks were utilized by Goh (1995a; 1995c) in order to capture the non-linear association between the relative density and the cone resistance from (CPT). Over- and typically cemented sands were studied in the research. The NN model was tested and trained using laboratory data and calibration chamber experiments. The model returned correlation values of 0.91 and 0.97 for the testing and training data, respectively [13]. As a result, the non-linear connection between CPT cone resistance and the other parameters could be well modeled by the neural network model.

IV. SIGNIFICANCE TO THE U.S

Construction sector operations will be reshaped significantly by the use of artificial intelligence (AI). It is possible for construction companies to succeed by incorporating AI-powered technologies. The growth of AI might be greatly supported by cutting-edge hardware, such as intelligent sensors, virtual reality systems, and other tools, as well as by scientific research into the algorithms and simulation approaches that let machines learn from data without being directly programmed [14,15]. When compared to other subterranean engineering specializations, such as civil and mechanical underground engineering, tunnel and underground space engineering must contend with a greater number of unknowns because of the characteristics of the materials involved in the development and deposition of the subterranean structures. The use of artificial intelligence and machine learning is still necessary to make the most of the vast amounts of monitoring and site investigation data that are already available in engineering practice [16,17].

V. FUTURE IN THE U.S.

The future of AI and ML in the U.S will see a proliferation of technology, sensors, and monitoring tools that place data at the heart of geotechnical engineering projects as we go forward. New algorithms for geotechnical data will be developed by geotechnical engineers to fulfill the demands of current practice, exploit new possibilities presented by future technology, or meet the demands of the digital transformation [18]. Machine learning (ML) has recently piqued geotechnical engineers' attention due to its widespread usage in a variety of fields. Geological data collection techniques, rock classification methods, tunnel design studies, and tunnel building and maintenance operations will all be transformed by digitalization.

VI. CONCLUSION

This research paper discussed applications of Artificial Intelligence and Machine Learning in Geotechnical Engineering. This research shows that AI and ML can have a significant impact on geotechnical engineering. No one disputes that artificial intelligence (AI) models have been able to surpass or at least equal to traditional approaches. Non-linear interactions between inputs and output have been simplified by AI approaches, allowing for greater physical knowledge of diverse issues without the need for fundamental assumptions. Since the use of AI approaches is gaining traction, we can argue that geotechnical engineering is going toward a better and more hopeful future that is error-free and more precise. However, as is often the case in science and all of its applications, the expected outcomes should be reviewed with caution and space for uncertainty should be permitted. Based on input data alone, Artificial Neural Networks (ANN) are an AI-based technique that can anticipate outputs, behaviors, patterns, and maps Non-linear computational components are an advantage of the Artificial Neural Network (ANN). As a result, ANN's outputs are non-linear, have lower error, and are thus more accurate. ANNs were first developed in the 1990s and have subsequently been employed to solve almost every technical challenge. This suggests that ANNs have a bright future ahead of them. Geotechnical engineering challenges may be irregular and complicated, and artificial neural networks (ANNs) can help tackle these difficulties, although they have their own drawbacks. Over-fitting, the inability to exhibit a ransparent link between output and input parameters, and erroneous forecasts in the event of minor settlements are some of the main drawbacks of the ANN algorithm. In addition, the structure of an ANN network (model inputs, the number of hidden layers, etc.) must be predetermined and requires a lengthy, time-consuming process of trial and error.

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