Artificial Intelligence in Geotechnical Engineering: Applications, Modeling Aspects, and Future Predictions

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Abstract— *The main aim of this study is to explore how artificial intelligence is used in geotechnical engineering in terms of modeling and future forecasts. The geotechnical engineering field focuses on using soils and rocks in engineering structures. In material modeling, soils and rocks naturally display complicated behaviors and a high degree of uncertainty. Over the last three decades, more researchers in the area of geotechnical engineering have created and deployed artificial intelligence (AI) approaches [1]. The effectiveness of these techniques has been attributed to their capacity to forecast intricate nonlinear interactions. Complex geotechnical issues have lately seen an increase in the usage of artificial intelligence (AI) methods. These methods might be due to the inefficiency of the old approaches or the excellent prospects of modern methods to express such complexity [1]. Most fields of geotechnical engineering have used artificial intelligence. Artificial intelligence applications were thoroughly examined and addressed in this study, where they excelled in most of them.*

Keywords— ***Artificial intelligence, Materials modeling, soil mechanics, artificial neural network, geotechnical engineering, pile foundations, bearing capacity***

I. INTRODUCTION

The capability of artificial intelligence (AI) to anlyze with voluminous, incomplete, skewed, and even inaccurate data has made it one of the fastest-growing industries in the twenty-first century. It was the ideal instrument for handling geotechnical issues due to its capacity to tolerate input ambiguity. Each (AI) strategy has unique features, benefits, and drawbacks; this variety enables researchers to approach the same issue in many ways to determine the optimum technique for such a problem. In geotechnical engineering, ground elements, including soil, rock, and intermediate geo-materials like coal, are studied and used in construction projects [1,2]. Road paving, foundations, dams, landfills, earthquakes, mineral prospecting on the surface and below ground, and slope stability are just a few of the many applications where it's critical. In contrast to other engineering materials, soil structure is a three-phase system that reacts in a highly nonlinear way to changes in water content and ambient circumstances. This is because of the variations in their origins and formation processes. Soil and rock are naturally anisotropic and heterogeneous. Due to this high degree of variability, there is a limit to the analytical and numerical solutions developed for certain issues. The behavior of materials is generally studied using two primary methodologies in geotechnical engineering [2].

In the recent three decades, researchers in geotechnical engineering have been interested in AI-based modeling tools as a possible alternative. AI forecasts, monitors, identifies, discovers, and classifies various aspects. Ai technologies can correctly anticipate even when physical correlations between variables are unknown [2]. The advantages and current success of AI approaches in geotechnical engineering give impetus to examine and analyze previous publications in this domain. This research comprehensively assesses AI-based methodologies and explores the aspects that influence their use for geotechnical engineering applications. Geotechnical engineering has been the topic of previous review publications.

Consequently, several crucial issues that are important for the effective implementation of AI techniques and helpful for future study remain elusive. The quantity of data sets required to train an AI model, for instance, significantly impacts the model's accuracy. By examining the impact of data set size and type (experimental vs. numerical) on the effectiveness of AI-based models for geotechnical engineering, this research aims to close this gap[3]. The performance of AI techniques may be impacted by the input parameter choices used for any AI modeling.

II. RESEARCH PROBLEM

The main problem that this investigation will tackle is the question of how Artificial Intelligence operates in Geotechnical Engineering, its applications, modeling features, and future projections. When it comes to civil and geotechnical engineering, there are a wide range of concerns and challenges that are deeply affected by many unpredictable aspects that not only demand mathematical, mechanical, and physics understanding but also the experience of the practitioners. [3] Traditional methods cannot address these concerns and limitations. AI, on the other hand, is a powerful tool for solving these difficult problems. AI's place in civil engineering and construction was one of the study's primary objectives. Preliminary calculations are necessary for geotechnical and construction engineering to estimate attributes such as soil shear strength, concrete compressive strength, the project cost, and project time. These characteristics are used to ensure a structure's high quality, long life, dependability, robustness, and resistance to external forces [4].

III. LITERATURE REVIEW

A. *Overview of AI*

Traditional computational approaches have been unsuccessful in solving engineering challenges that conventional methods cannot solve. This is where artificial intelligence (AI) comes into play (Flood, 2008). Even if the physical meaning or the underlying linkages of the data are unknown, the subtle functional links among them may be captured by using AI algorithms to learn from instances of data inputs and outputs. Because AI models are data-driven, they do not predict how a system behaves physically. A fundamental difference between this and most physical models is the reliance on basic principles (such as physical laws) to deduce connections within the system, as opposed to more complex models that rely on previous knowledge of the relationships between variables. Compared to most empirical and statistical approaches, this is one of the key advantages of AI techniques. [4] The AI model's approach mirrors several traditional statistical models, which aim to explain relationships between model inputs and their predicted outcomes[5]. Machine learning is used to determine the function y5f(x) that minimizes the expected between the recent outputs and the outputs projected by the AI model [5]. If x and y have a nonlinear connection, only previous knowledge of the non-linearity will allow statistical regression analysis to be used effectively. For AI models, previous knowledge of the non-nature linearity is not necessary. Traditional regression techniques are ineffective when dealing with complicated and extremely nonlinear issues in the real world.

B. Applications of AI in Civil Engineering

Applications of Artificial Intelligence in Civil Engineering AI models are utilized in civil engineering to create construction projects that are more accurate, less expensive, and less disruptive. In today's buildings, artificial intelligence determines how electrical and plumbing systems will be routed throughout the building. Artificial intelligence (AI) is now being used at construction sites to monitor real-time interactions between workers, machines, and other things on the job site and to identify possible construction mistakes, safety dangers, and productivity issues. To make things easier for people in the development industry, simulated intelligence makes it more logical. As a result, structural designers have more options since it's an interesting area of work [6].

i. Artificial neural networks (ANNs)

Artificial intelligence (AI) includes technologies such as the artificial neural network (ANN). The idea of an artificial neural network (ANN) is not new and is based on how neurons in the human brain function [7,8]. ANNs are used when trying to solve issues that are too complicated to be analytically defined. One kind of artificial intelligence is known as artificial neural networks, whose goal is to simulate how the human brain cells operate. The backpropagation training technique for feed-forward multilayer perceptrons (MLPs) was released in 1986. However, ANN is a concept that was originally described in 1943. ANNs have been extensively studied by a wide range of researchers [8]. To build an ANN, you'll often need many processing elements (PEs), which are placed in a hierarchy: an input layer, an output layer, and sometimes even a layer that isn't visible to the user. A neural network (ANN) comprises neurons, basic processing units, and weighted connections that link them all. It may be described as a huge, parallel dispersed network of simple things, known as neurons, that process data in a distributed manner. It naturally has a predisposition to accumulate experience knowledge, which is subsequently employed, similarly to how the brain gathers and stores information [9]. Through the strength of neuronal interaction, the neural network learns and retains information throughout the learning process [9,10]. The architecture of neural networks makes it feasible to solve problems without the help of specialists or programming. They are specially designed for difficult issues with no formal underpinning theories or traditional mathematics and standard techniques, and they often hunt for patterns and relationships in ambiguous data. Regression sampling is one statistical and algorithmic approach that ANN varies from since ANN learns from instances to provide generalized answers.

ii. Applications of artificial intelligence in geotechnical engineering

The major components of AI applied in geotechnical engineering prediction are knowledge-based expert systems and neural network techniques. Numerous geotechnical engineering features, including rock and soil parameters, constitutive connections, settlement predictions, bearing capacity, liquefaction, long-term pavement performance, and rock fall and slope stability assessments, are predicted using AI systems. AI applications to rock slope stability is a challenging issue that affects all of us and is rife with ambiguity. Rock slope instability on roads and highways may lead to hazardous circumstances and financial and functional losses in many transportation situations. To effectively manage rock slope failure, the potential is mapped for the public, and private users are mapped [11]. AI techniques to determine the slope failure potential maps is a quick, useful, and economic strategy. Due to the unpredictability of expert judgments, AI systems are used to assess the failure probability of slopes. The prediction of slope instability through geographic information system (GIS) databases is employed as a platform [11]. The process is started based on the geology, topography, and other data entered into the GIS database. Once the failure potential of slopes has been determined, the AI system starts modeling the complicated issue utilizing the known connection between the model variables to produce maps showing the slope failure potential. By prioritizing the follow-up operations to solve the issue, such as directing more in-depth investigations and choosing efficient methods to monitor and set up an early-warning system, the slope failure potential maps created using AI systems also improve slope management.

Modeling components

iii. Uses of artificial intelligence in pile foundations

AI models for geotechnical engineering challenges, such as pile foundations, many elements in the application of AI approaches need to be rigorously investigated[12]. An acceptable model input considers variables like determining the best way to divide data and prepare it for modeling and ensuring that the models are robust, transparent, and easy to extract information about. Some of these variables have recently attracted attention, while others need further study.

Soil and rock, for example, display a wide range of behavior due to the imprecise physical processes involved in their production, which is why geotechnical engineering must deal with such materials. Structures are supported by foundations, which distribute the pressure to geological formations or soil with enough load carrying capacity and good settling properties. Various foundations are available, each suited to a certain use. A pile is a large, solid cylindrical structure driven into the ground to serve as a firm foundation for constructions sitting on top of it. For the most part, piles are broken down into two distinct categories. Non-displacement and replacement piles are two different types of piles.

Displacement of piles occurs when the soil is moved vertically and radially when the piles are pushed into the ground.

If you need Replacement piles, the earth has to be drilled, and the dirt is removed before a block of concrete or pre-cast concrete pile is put in its place. As a result, standard approaches of physically-based engineering often cannot model the behavior of geotechnical engineering piles. Most pile foundations can be modeled using artificial intelligence (AI) because of its capacity to forecast the complicated behavior of these structures better than conventional approaches [12].

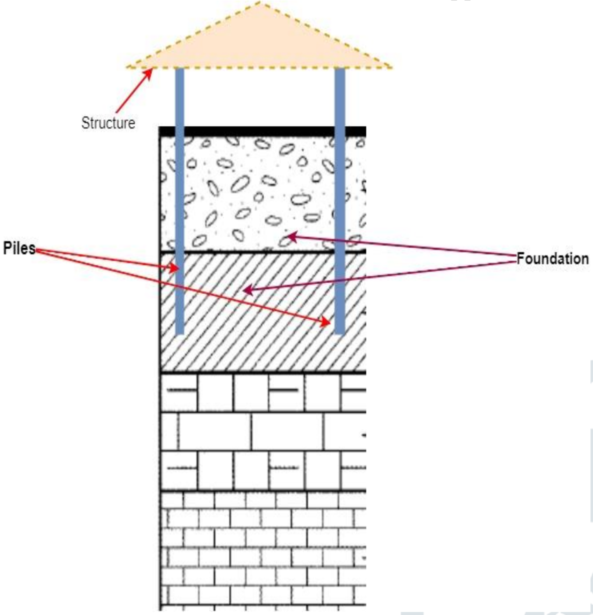

Fig i: A pile Foundation

Pile foundation design requires accurate calculations of pile load capacity and settling. In the past, the design of a structure's bearing capacity and settlement was done independently. In addition, since soil resistance and settlement are interdependent, the design of pile foundations must take these factors into account. Pile load-settlement behavior must be accurately anticipated for this to work. Nevertheless, it is generally recognized that costly and time-consuming in-situ stress testing is the only way to accurately determine how pile foundations behave under loads. We can simulate the whole load-settlement mechanism of steel-driven piles under axial loads by employing artificial intelligence (AI) powered by recurrent neural networks (RNN). Many in-situ entire load -settlement experiments and findings from cone penetration tests (CPT) are used in calibrating and validating the constructed RNN model. RNN model can accurately forecast axially loaded steel-driven pile load-settlement behavior and may be utilized for engineering purposes in everyday design practices.

iv. Prediction of bearing capacity

It is common practice to employ shallow or spread-out foundations to transmit the column-load of small to moderate elevation constructions to the subsurface. The determination of soil bearing capacity, a foundation's pressure gradient may impose on the soil to meet sufficient considerations against shear failure, and appropriate total and differential settlements are considered. The minimal force required to tear the supporting soil directly underneath and next to the foundation is known as the ultimate bearing capacity. When constructing buildings on soil, they consider the shear strength, porosity, penetration, frictional resistance, and other elements. Engineers utilize their best judgment when doing many of these tests and computations to determine the carrying capacity of the soil. The engineer must decide where to begin and end the measurement to determine the effective length. An engineer can decide to utilize the pile depth as one technique, after which they will deduct any disturbed underlying soils or combinations of soils. Geotechnical Engineers may alternatively quantify it as the height of a single pile portion in a particular layer of earth comprising numerous layers.

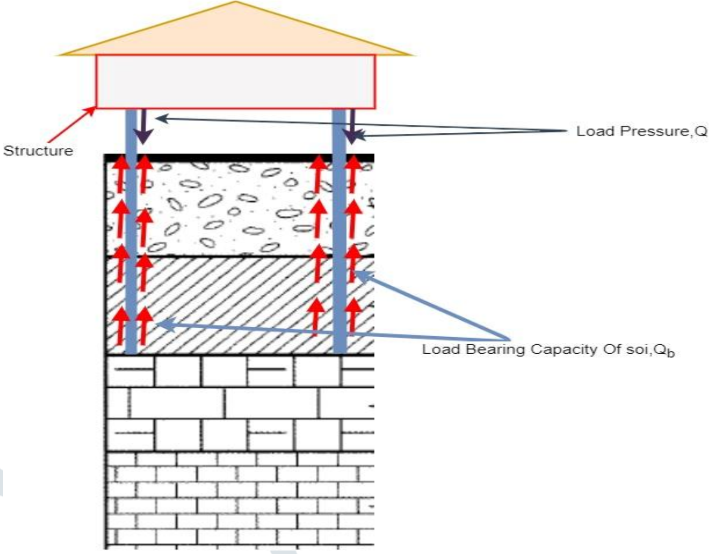

Fig ii: Illustration of the Load Bearing Capacity of the soil

Two key factors influence foundation design: bearing capacity and settling. Predicting how much weight the foundation can bear is a major consideration for pile foundations and has been studied by many AI researchers, particularly those employing neural networks. For instance, [13] reported a neural network method to estimate the frictional performance of soil piles, which was analyzed using fieldwork data from accurate case records. Inputs into the simulation were the pile height, thickness, average pressure distribution, and unconfined compression strength. The only data that the prediction made was the friction factor barrier. Comparisons are made between the neural network model's findings and those derived using the approach [14]. Coefficients of correlation and error rates between anticipated and measured bearing capacity capacities were utilized as performance metrics. Existing techniques are inferior to ANN models. The maximum load capacity of pile foundations in non-cohesive soils was estimated to use another neural network model created shortly after [14]. Tests on piles constructed of wood, pre-cast steel, and concrete pushed into fine sand yielded the evidence for this report's results. Hammer load, impact and design, pile height, load, cross-sectional diameter, stiffness, and elastic modulus were more critical elements to the ANN model. The capability of the pile to support loads was the result of running the model [14]. After putting the model through its paces with a test dataset, the finding is that the prediction model anticipated the maximum pile load. Determining which criteria are essential in structural weights is necessary to examine pile sets and hammer weights and types. As opposed to traditional backpropagation ANN, Bayesian ANNs provide a probability distribution across the anticipated value [14,15] rather than simply one prediction. This distribution can provide information on the typical forecast error resulting from the uncertainty involved in extrapolating noisy data. It also makes it possible to gauge the degree of confidence in a given forecast.

IV. SIGNIFICANCE TO THE U.S

The United States can utilize artificial intelligence successfully in various applications within geotechnical engineering, particularly predictions and risk assessment. The application of artificial intelligence in geotechnical engineering is crucial for the building, upkeep, and administration of numerous aspects of civil infrastructure. The U.S is now developing AI applications like robots, augmented reality, and virtual reality are all going to be valuable in geotechnical projects, especially the construction of pile foundations and determining the bearing load capacity. This process will make geotechnical engineering more popular in the civil engineering industry as an occupation that many people will be willing to undertake [16]. Artificial intelligence (AI) innovation is significant in automating various features of civil and geotechnical engineering works. Some typical applications include predicting concrete compressive strength, modulus of soil rupture, construction pre-cost and timeframe, predictive maintenance, deformation identification, and pothole identification. Any nation, whether it is still growing or well established, may look on the construction sector to significantly contribute to the economy's growth. The amount of time spent, money spent, and quality of work done on infrastructure projects are the driving forces behind the growth of this industry. The initial set of observable variables is used to estimate and forecast pre-construction outputs to guarantee process performance, expenditure, and execution [16,17]. Because it is common knowledge that building projects are prone to problems like cost overruns, delays in completion, and collapse of buildings as a result of inaccurate estimations of key parameters, in hopes of avoiding these frequent problems from happening in any construction project, the previous calculation, and forecast of variables such as budget, durability, and the nature of the soil that is being used must be done.

V. FUTURE IN THE UNITED STATES

The implementation of artificial intelligence will unquestionably make life simpler in the United States in the future, and it may even inspire people to increase the breadth and depth of their skill sets. Because of advancements in AI technology, the job of builders and architects is becoming much easier. The advancements in technology associated with AI will also contribute to creating new employment, as we will need a greater number of engineers to conduct research, design, and test AI systems [18]. These techniques are a fantastic opportunity for the engineering community to demonstrate our ingenuity in artificial intelligence (AI) developments while contributing to the system's overall growth and efficiency [19]. For example, building well-maintained roads is one of the significant factors contributing to the delivery of a safe and unobstructed driving experience. Before building roads, it is necessary to consider various aspects like the amount of money to be spent, the amount of time and labor required, and the kind of material used. Using AI and computer vision methods, this early computation of road construction characteristics may be automatically generated with zero to little human interaction in the age of machine learning [19]. Calculating parameters using a machine enables not only a reduction in the amount of time and expense necessary but also an improvement in the accuracy of their computation due to the removal of all forms of human mistakes.

VI. CONCLUSION

This research sought to analyze the use of artificial intelligence applications, modeling, and prospects in geotechnical engineering was assessed in this paper. The use of artificial intelligence and the models it generates may also be observed in the realm of building. Creating intricate, powerful, and aesthetically pleasing buildings often calls for a high degree of accuracy and competence to be used in construction jobs. Any mistake can result in losses not just in terms of people's lives but also in terms of property and infrastructure. As a result, AI models may be used in the performance of various activities in construction and geotechnical engineering, particularly those that need a high level of accuracy and precision. When it comes to civil and geotechnical engineering, there is a wide range of opportunities and issues that are deeply affected by many unpredictable aspects that not only demand mathematical, mechanical, and physics understanding but also the expertise of the professionals. The standard operating procedures are ineffective for addressing these problems and difficulties. However, employing AI to handle these difficult problems is rather straightforward.

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