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Opinion Article

The Role of Artificial Intelligence in Geotechnical Engineering: Applications, Optimization Strategies, Modeling Approaches, and Future Prospects

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Abstract

The principal objective of this study is to examine the utilization of Artificial Intelligence (AI) in geotechnical engineering, emphasizing modeling methodologies and prospective forecasts. Geotechnical engineering, which deals with the utilization of soils and rocks in building, often faces complicated behaviors and a high degree of uncertainty in material modeling. Over the past few decades, the integration of AI techniques has gained momentum, giving solutions to forecast sophisticated nonlinear interactions within the field. These AI technologies have emerged as powerful tools in addressing difficult geotechnical challenges, overcoming the limitations of previous methods due to their capacity to capture and anticipate complicated events with precision. As the worldwide impact of climate change continues to grow, the demand for sustainable technology in engineering processes has become more essential. Artificial intelligence offers a means to diminish dependence on conventional laboratory techniques, which frequently generate carbon emissions. AI approaches specifically improve the accuracy and efficiency of earthwork design and construction, thereby diminishing environmental impact by decreasing material usage errors. This paper analyzes several AI techniques-such as Artificial Neural Networks (ANN), Fuzzy Logic, Genetic Programming (GEP), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Analysis of Variance (ANOVA)-and their applications in solving geotechnical and geo-environmental challenges. These new approaches address the limitations of conventional experimental protocols, guaranteeing more sustainable, precise, and environmentally friendly solutions in geotechnical practice. This comprehensive analysis shows the expanding relevance of AI in geotechnical engineering, providing a significant resource for future researchers wanting to leverage intelligent algorithms in enhancing the efficiency, precision, and sustainability of engineering models. By embracing these solutions, the field can drastically reduce the environmental effect associated with traditional geotechnical operations, contributing to a more sustainable and carbon-conscious future

Introduction

The ability of Artificial Intelligence (AI) to analyze vast, incomplete, biased, and even erroneous data has become it one of the most rapidly expanding sectors in the twenty-first century. It was the optimal tool for addressing geotechnical challenges due to its ability to accommodate input uncertainty. Each (AI) strategy has unique features, benefits, and downsides; this variety enables researchers to approach the same topic in many ways to identify the ideal solution for such a problem [1]. Geotechnical engineering examines ground elements such as soil, rock, and intermediate geo-materials like coal, which are utilized in construction projects. Road paving, foundations, dams, landfills, seismic activity, surface and subsurface mineral exploration, and slope stability are among the several uses where it is essential [2]. In contrast to other engineering materials, soil structure is a three-phase system that reacts in a highly nonlinear fashion to changes in water content and ambient circumstances. This is because to the variances in their origins and production processes. Soil and rock have inherent anisotropy and heterogeneity. The significant variability imposes constraints on the analytical and numerical solutions provided for specific problems. The behavior of materials is often studied using two basic techniques in geotechnical engineering [3]. In the recent three decades, academics in geotechnical engineering have been interested in AI-based modeling tools as a feasible alternative. AI predicts, observes, recognizes, uncovers, and categorizes diverse elements. AI technologies can correctly anticipate even when physical correlations between variables are unknown. The benefits and present achievements of AI methodologies in geotechnical engineering necessitate the examination and analysis of prior publications in this field [4]. This review fully examines AI-based methodologies and explores the elements that influence their utilization for geotechnical engineering applications. Consequently, numerous fundamental topics that are vital for the effective deployment of AI approaches and valuable for future study remain unclear.

Overview of AI

Traditional computational approaches have been unsuccessful in solving engineering difficulties that conventional methods cannot tackle. This is where Artificial Intelligence (AI) comes into play [5]. Even if the physical meaning or the underlying linkages of the data are unknown, the subtle functional links among them may be captured by utilizing AI algorithms to learn from examples 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 primary advantages of AI techniques [6]. The AI model's approach matches various traditional statistical models, which try to explain correlations between model inputs and their expected outcomes. Machine learning is utilized to determine the function y5f(x) that minimizes the predicted between the recent outputs and the outputs projected by the AI model. If x and y have a nonlinear connection, only previous knowledge of the non-linearity will allow statistical regression analysis to be applied effectively. For AI models, preexisting knowledge of the non-nature linearity is not necessary. Traditional regression procedures are ineffective when dealing with complicated and severely nonlinear issues in the real world [7].

Applications of AI in Civil Engineering

Applications of Artificial Intelligence in Civil Engineering

AI models are applied 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 humans, machines, and other things on the job site and to identify prospective construction blunders, safety dangers, and productivity concerns. To make things easier for people in the development sector, simulated intelligence makes it more logical [8]. As a result, structural designers have more possibilities as it's an intriguing field of work

Artificial neural networks (ANNs)

Artificial Intelligence (AI) encompasses technology 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 behave. ANNs are utilized when trying to address challenges that are too complicated to be analytically defined. One sort of artificial intelligence is known as artificial neural networks, whose purpose is to imitate how the human brain cells behave. The backpropagation training technique for feedforward Multilayer Perceptron's (MLPs) was released in 1986 [9]. However, ANN is a concept that was originally articulated in 1943. ANNs have been intensively explored by a wide range of researchers. To design an ANN, you'll generally require many processing elements (PEs), which are organized in a hierarchy: an input layer, an output layer, and occasionally even a layer that isn't visible to the user [10]. A Neural Network (ANN) comprises neurons, fundamental processing units, and weighted connections that link them all. It may be described as a massive, parallel dispersed network of basic entities, called as neurons, that process data in a scattered fashion. It naturally has an inclination to accumulate experiential knowledge, which is subsequently employed, comparable to how the brain acquires and stores information. Through the strength of neuronal interaction, the neural network learns and retains information throughout the learning process. The architecture of neural networks makes it feasible to solve problems without the intervention of specialists or programming [11]. They are specially developed for difficult challenges with no formal supporting theories or traditional mathematics and standard methodologies, and they often hunt for patterns and linkages in unclear data. Regression sampling is one statistical and algorithmic approach that ANN differentiates from since ANN learns from cases to provide generalized responses [12].

Background

In the past two decades, Artificial Neural Network (ANN) has been one of the primary interests in structural engineering, environmental and water resources engineering, traffic engineering and geotechnical engineering. ANNs represent a class of robust, non-linear models appropriate for tackling a wide spectrum of complicated technical challenges. Engineering challenges that entail highly nonlinear functional approximations could be tackled utilizing ANNs. Artificial Neural Network (ANNs) may be defined as a structure of tightly coupled adaptable simple processing elements (named artificial neurons or nodes) which are able to do large-scale parallel computations for data processing and knowledge representation (Huang et al., 2019). In 1943, McCulloch and Pitts (1943) proposed the first artificial neuron model (MP model), which employed simplified signal propagation mechanism to simulate some basic operations of human brain neurons, thereby laying the groundwork for the development of early neural computing [13]. A study presented one of the first journal articles on the civil/structural engineering uses of neural networks. Since then, neural network has been frequently used in civil engineering. ANN is a form of technical reconstruction of biological neural network in a simplified sense. Its major job is to develop a practical artificial neural network model according to the principle of biological neural network and the necessity of practical application, design corresponding learning algorithm, and replicate some intelligent behaviors of human brain. Finally, it is implemented technically to solve practical difficulties. An artificial neural network (ANN) is a computational model which seeks to imitate the functional elements of biological neural networks [14].

ANNs consist of connected artificial neurons that process information using a connectionist approach. ANNs are used to correlate inputs and outputs by continually increasing connections weights according to inputs-outputs. They can be used to describe complex interactions between inputs and outputs or to detect patterns in data (Salahudeen et al., 2020). Complicated interactions between outputs and inputs could be uncovered by adjusting model architect and linkages weights. Although apart from these advantages, ANNs have a big disadvantage; they do not generate a closed form formula [15]. Developing procedure of ANN model involves six steps. These are: selecting variables (input & output), collecting of database and split it into training and validating groups, determining the network architect, optimizing of links weights, terminating of training based on preset criteria and validating of the correctness of the ANN.

Artificial Neural Network (ANNs) are a form of artificial intelligence which seek to emulate the behavior of the human brain and nervous system. The common architect of ANN includes two layers (input & output) and number of hidden layers between them. Input layer has a number of nodes equal to the input variables, output layer has a number of nodes equal to the output variables, while each hidden layer has a predetermined number of nodes based on the intricacy of the relationship [16]. Each node aggregates its inputs from the linked nodes from the previous layer multiplied by the weight of each connection, nonlinear activation function is applied to that total to form the output of the node which will be the input of the linked nodes in the following layer. Information propagates off in the ANN from the input layer to the output layer through the hidden layers. During training (learning) process, the weights of the linkages are tuned to reduce the prediction error using the training database. After training process, the accuracy of the trained ANN must be validated using independent validation database. ANNs learn from data examples supplied to them and utilize this data to update their weights in an attempt to reflect the link between the model input variables and the corresponding outputs [17]. Consequently, ANNs do not need any prior knowledge about the nature of the relationship between the input/output variables, which is one of the benefits that ANNs have compared with most empirical and statistical methods. The ANN modelling concept is comparable to a variety of conventional statistical models in the sense that both are seeking to describe the relationship between a historical collection of model inputs and related outputs. ANNs can form the simple linear regression model by having one input, one output, no hidden layer nodes and a linear transfer function. ANNs modify their weights by repeatedly presenting instances of the model inputs and outputs in order to minimize an error function between the historical outputs and the outputs predicted by the ANN model [18].

Artificial Neural Networks take their name from the networks of nerve cells in the brain. Although they offer a much-simplified version of the human brain, still these computational models inspired by biological neural network may provide new avenues to handle complicated problems. In contrast to digital computers, which enable sequential processing of information, ANNs parallel processing inspired by working of a human brain, gives computers an additional advantage to simultaneously handle massive volumes of data [19]. ANNs are highly suited for problems whose solutions involve knowledge that is difficult to express but for which there are enough data or observations. The neural network's ability to learn from experience without seeking prior knowledge about the governing relationships and to generalize when confronted with unseen data provides the backbone of its modelling abilities, with which it approximates any functional relationship with reasonable accuracy. It has been claimed that the ANN has the ability to extract the patterns in phenomena and overcome the obstacles associated to the selection of the model form, such as linear, power, or polynomial. The unifying elements of some of these successful uses of ANNs in prediction and modelling are that the quantities being modelled are regulated by multivariate interrelationships and the data provided [20].

A study characterized neural networks as a massively parallel distributed processor made up of simple processing units, which has a natural predisposition for storing experiencing information and making it available for application. Neurons are the basic units employed for computation in the brain, and their simplified abstract models are the basic processing units of ANNs. In addition to the processing elements called "neurons", the neural networks incorporate the connections between the processing elements. The connections have a "weight" value denoting the relevance of the relationship between the neurons [18]. The synaptic weights store the knowledge of the neural networks and therefore in the training phase with a continuous flow of information, there is a gradual reorganization of weights within the neural network and subsequent comparison of target and predicted values in an attempt to reduce the network error to a minimum. The constant update of synaptic weights is accomplished via a learning method termed error back-propagation. Back-propagation provides a computationally fast way for adjusting the weights in a feed forward network, with differentiable activation units to learn a training set of input-output samples. ANN is classed as "black box system", because its links weights, parameters and operations are hidden from users. Besides that, insufficient database may create a bad generalization. Backpropagation ANN was used to estimate the residual friction angle of clay utilizing its consistency limitations (LL, PI, CF and ΔPI), additionally, the relative relevance of each input was examined [21].

Fuzzy Logic (FL)

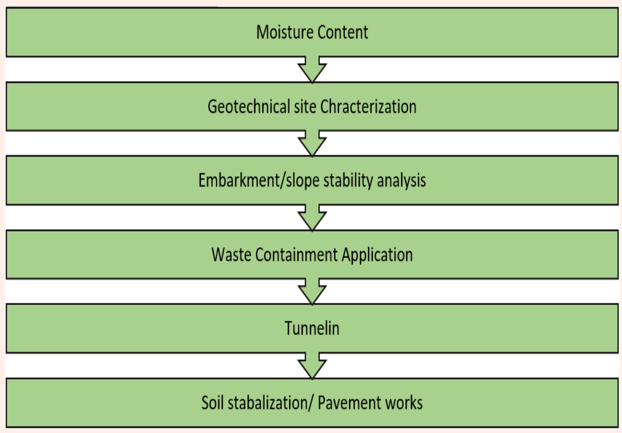
Any technique or methodology engaged in making the greatest or most effective use of a situation or source could be characterized as optimization. It might be regarded as a search for another technique with the utmost attainable performance under a set of stated limitations by maximizing desired variables and reducing undesirable variables in order to reach the needed maximum outcome without regard to cost or effort [22]. Nature inspired/artificial intelligence techniques (biomimetics) extensively do not detail the physical mechanisms for the problems being addressed. Mathematical computations have been employed over the years for engineering optimization processes. For any algorithm optimization to work properly three conditions must be met; there has to be: (1) an objective function. (2) Constraints and (3) A collection of data to test the algorithm. However, due to saturation in the use of these methods, and because of the complexity associated with civil engineering problems, researchers explored the use of nature inspired/artificial intelligence optimization algorithms in applications such as earthquake engineering [23].

Applications of Fuzzy Logic

Generally, geotechnical engineering problems are packed with imprecise, ambiguous and incomplete information. In most situations, such challenges are successfully solved by expertise and experience of relevant specialists. Artificial intelligence has been utilized to replicate the decision-making procedures comparable to that of human brain to aid the geotechnical specialist's choice of solution to practical challenges regarding the construction of retaining walls and estimation for length of slurry walls. The Fuzzy Logic (FL) which is built on a natural language that is supposedly stress-free to understand could be flexible and lenient on imprecise facts. It can also simulate non-linear functions of random complexity in geotechnical problems.

The FL approach comprises knowledge-based models which leverage human intuitive reasoning viewed as being biased and inaccurate [24]. Artificial intelligence has been used in geotechnical engineering applications that include: the correlation of soil properties, soil classification and profiling, detailed rock properties (e.g., shear, tensile and compressive strength, elastic modulus and density as well as electrical conductivity), slope stability, soil compaction, soil-water interaction, soil behaviour and modelling under loads, prediction of the deformations beside braced deep excavation, estimating the stability of retaining structures, selection of optimum shoring technique, prediction of settlement due to tunnelling, soil liquefaction appraising the ultimate bearing capacity for shallow and deep foundation [25].

Figure 1: Applications of Fuzzy Logic.

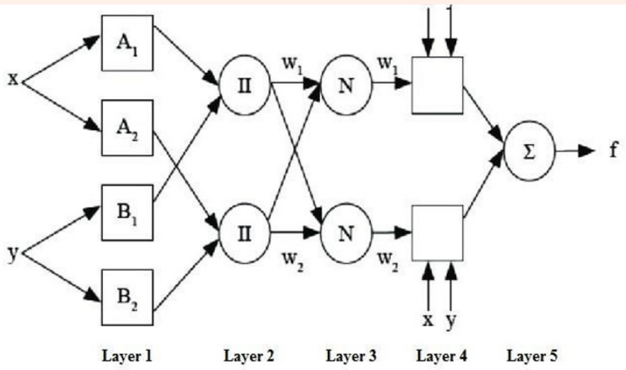


Adaptive Neuro Fuzzy Inference System (ANFIS) and its Application in Civil Engineering

The ANFIS model possesses the advantage of integrating both numerical and language knowledge. ANFIS also employs the ANN's capacity to classify data and discover patterns. In comparison to the ANN, the ANFIS model offers greater transparency to the user and results in fewer memorization errors. ANFIS formulates an information yield planning model that integrates human knowledge (as fuzzy logic standards) with empirical input-output data sets through the application of least squares estimations. After produced input-yield via preparing, the ANFIS can be employed to perceive information that is similar any of the models exhibited during the preparation step [26]. The majority of issues addressed in civil and structural engineering with ANFIS include predicting behavior based on the experimental results utilized for training and testing data. The matter of modeling is to solve a problem by forecasting which is obtained by mapping a collection of variables in input space to a set of response variables in output space through a model, generally a mathematical model is utilized. Nonetheless, the traditional modeling of the underlying processes frequently becomes exceedingly intractable and challenging. A novel technique to modeling has recently arisen, characterized as soft computing, primarily involving neural networks and fuzzy logic. The construction of these models, however requires a set of data. Fortunately, for many problems of civil engineering such data are available [27].

The ANFIS system consists of five network layers that describe multi-layered neural networks (NN) and have various goals for each layer, which consists of multiple nodes represented by squares or circles and have distinct roles for each layer. The circle symbol depicts a non-adaptive node whose value is fixed, while the box sign denotes a adaptive node whose value can change with learning.

Figure 2: Civil Engineering data.



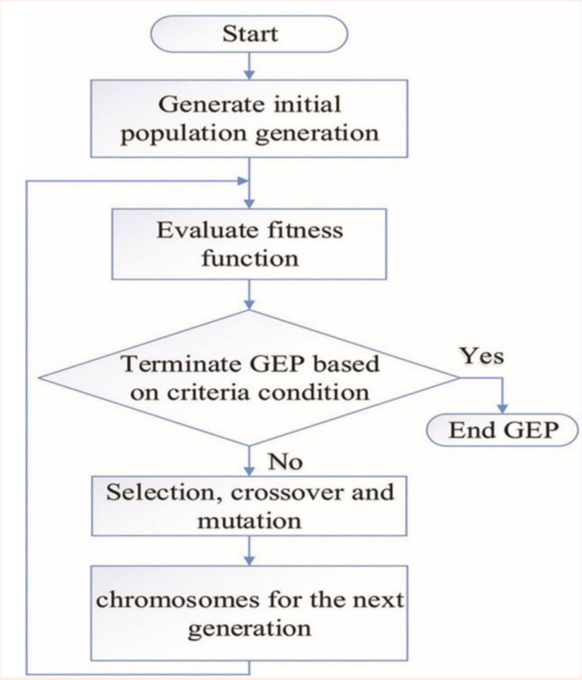
Gene Expression Programming (GEP)

GEP is a type of evolutionary algorithms inspired by biological systems; the system is a full-fledged genotype/phenotype system with expression trees of varied sizes and shapes encoded in linear chromosomes of fixed length. Though almost like GAs and GPs, GEP chromosomes are multi-genic, encoding several expression trees or sub-programs which will be organized into a significantly more complex program with operational flowchart. So, just like the DNA/protein system of life on earth, the genes/trees system of GEP can not only explore all the paths in the solution space but it is also absolving to explore higher levels of organization [23]. GEP has two key players; the chromosomes and also the Expression Tree (ET), these can further be classified as genotype and phenotype accordingly. The genotypes are chromosomes which are simple entities; linear, compact, relatively small, easy to change genetically whereas the phenotypes are exclusively the expression of their particular chromosomes. They are the creatures upon which selections acts and according to fitness they are selected to reproduce with alteration. The interplay of chromosomes (genotype) and expression trees (phenotype) in GEP demands an unequivocal translation mechanism for translating the language of chromosomes into the language of Expression Trees (ETs) [28]. The implementation of GEP permits that the chromosome to have more than one gene. These genes contain two types of information, the first type is stored in the head of the gene holding the data which is employed in constructing the overall GEP model and the second is saved in the tail of the gene and used to produce future GEP models. For every problem, the length of the head h is chosen, whereas the length of the tail t is a function of h and the number of arguments n of the function with more arguments (also called maximum arity) and is evaluated by the equation:

$$t = h\,(n-1)+1$$

The method starts with randomly creating chromosomes of a certain number of individuals (starting population) [29]. Then these chromosomes are expressed, and therefore the fitness of every individual is evaluated against a set of fitness scenarios. Then, the individuals are picked in line with their fitness to reproduce with alteration. These new individuals are subjected to identical developmental processes such as expression of the genomes, confrontation of the selection environment, selection, and reproduction with alteration. The process is repeated for a specific number of generations or until a good solution is identified. The terminal set includes of the independent variables that are considered as input variables of the model. So, the first step to use the GEP approach is to define the terminal set [30]. An evolutionary process is employed in the GEP technique for finding the optimum program and individual chromosomes are updated and optimized in each iteration depending on the fitness function and genetic operators like the genetic algorithm. This technique is repeated until the convergence criteria are achieved [31].

Figure 3: Gene Expression Programming.



The technique known as Gene Expression Programming (GEP) makes use of population in this case population of models and solutions, selects and reproduces them according to fitness, and introduces genetic variation using one or more genetic operators such as mutation or recombination (Mitchell, 1998). Though the GEP can be likened to the GA and GP as the two still operates on the principle of population, the fundamental distinction among the three algorithms is dependent on the nature of the individuals or models or solutions as the case may be; in GA the individuals are symbolic strings of fixed chromosomes, in GP the individuals are non-linear entities of different sizes and shapes while in GEP the individuals are encoded in symbolic strings of fixed chromosomes which are expressed as GPs, this means that GEP is a combination of GA and GP.

Analysis of Variance (ANOVA)

Analysis of Variance (ANOVA) is tool used for statistical analysis which separates an observed aggregate variability contained inside a data set into random and systematic elements. The random factors do not influence a specific data set statistically, while the systematic factors do. Thus, Scientists in different field of study make use of the ANOVA test for the determination of the effect that independent variables have on the dependent variable in a statistical regression investigation [32]. The variables that are measured are called the dependent variables whereas; the variables that are controlled/ manipulated are called independent variables or factors. ANOVA is an extension of the t -and z-tests and it is also called the Fisher analysis of variance. It is used to investigate if significance difference exists between the mean of two or more groups. The assumptions used in ANOVA are that the underlying distributions are normally distributed and that the variances of the distributions being compared are comparable [33]. The formula for ANOVA is given as:

$$F = MSE/MST$$

Where,

F = ANOVA coefficient

MST = Mean sum of squares between the groups due to treatment

MSE = Mean sum of squares within the groups due to error

ANOVA is commonly used to generate the F-value and p-value from the data set of an experimental sample. The F-value and p-value are used to examine the significance of the specified regression models at a 95% significance level. When there is no real difference exists between the tested groups, which is called the null hypothesis, the outcome of the ANOVA's F-ratio statistic will be close to 1. In ANOVA analysis, p-value is an important metric to examine since it reflects the probability that the outcomes of the analysis may have occurred by chance. When the p-value is greater than 0.05, the null hypothesis would be accepted whereas, if the p-value is less than 0.05, the null hypothesis would be rejected and the alternative hypothesis would be accepted [34]. ANOVA analysis can be undertaken using statistical tools like Microsoft Excel and Minitab. The sums of squares in the outcome of ANOVA analysis is segregated into distinct categories.

Applications of artificial intelligence in geotechnical engineering

The key components of AI utilized in geotechnical engineering prediction are knowledge-based expert systems and neural network approaches. Numerous geotechnical engineering aspects, including rock and soil parameters, constitutive connections, settlement forecasts, bearing capacity, liquefaction, long-term pavement performance, and rock fall and slope stability assessments, are anticipated using AI systems. AI applications to rock slope stability is a challenging issue that impacts all of us and is filled with uncertainty. Rock slope instability on roads and highways may lead to hazardous circumstances and financial and functional losses in many transportation settings [2]. To successfully manage rock slope failure, the potential is mapped for the public, and private users are mapped. AI approaches to predict the slope failure potential maps is a quick, useful, and economic strategy. Due to the unpredictability of expert opinions, AI algorithms are used to assess the failure likelihood of slopes. The prediction of slope instability utilizing Geographic Information System (GIS) databases is applied as a platform. The procedure 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 employing the known link between the model variables to produce maps displaying the slope failure potential [35]. By prioritizing the follow-up activities to fix the issue, such as directing more in-depth investigations and choosing efficient methods to monitor and build up an early-warning system, the slope failure potential maps developed using AI systems also improve slope management [36].

Table 1: The sums of squares in the outcome of ANOVA analysis is segregated into distinct categories.

AI Technique	Applications in Geotechnical Engineering	Advantages	Limitations
Artificial Neural Networks (ANN)	Predicting soil behavior, load capacity, settlement	Good for nonlinear problems, adaptable	Requires large datasets, black-box system
Fuzzy Logic	Soil classification, risk assessment	Handles uncertainty, flexible	Requires expert knowledge for rules
Genetic Programming (GEP)	Optimizing geotechnical designs	Can handle complex optimization tasks	Computationally intensive
ANFIS	Modeling soil-pile interaction, deformation prediction	Combines fuzzy logic and neural networks	May struggle with high-dimensional problems
ANOVA	Statistical analysis of soil properties	Simple, interpretable	Not suited for complex non-linear models

Table 2: Slope failure potential maps developed using AI systems also improve slope management [36].

Geotechnical Application	AI Technique Used	Objective
Slope Stability Prediction	ANN, GEP, GIS	Predicting slope failure and risk assessment
Pile Foundation Design	ANN, Fuzzy Logic, RNN	Estimating pile load-settlement behavior
Soil Behavior Modeling	ANFIS, ANN	Predicting soil response under loading
Bearing Capacity Prediction	ANN, GEP, Bayesian Neural Networks	Determining foundation capacity

Uses of artificial intelligence in pile foundations

AI models for geotechnical engineering challenges, such as pile foundations, various factors in the use of AI approaches need to be systematically investigated. An appropriate model input incorporates variables including finding the best approach to partition data and prepare it for modeling and ensuring that the models are resilient, transparent, and easy to extract information from [37]. Some of these variables have recently attracted attention, while others need further study. Soil and rock, for example, demonstrate 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 transmit the pressure to geological formations or soil with enough load carrying capacity and good settling qualities. Various foundations are available, each suited to a given application. A pile is a massive, solid cylindrical structure pushed into the ground to serve as a stable foundation for constructions sitting on top of it. For the most part, piles are split down into two distinct groups. Non-displacement and replacement piles are two different types of piles [38]. Displacement of piles happens when the earth is moved vertically and radially when the piles are pushed into the ground. If you need Replacement heaps, the ground has to be drilled, and the dirt is removed before a block of concrete or pre-cast concrete pile is installed in its place. As a result, typical ways. Because physically-based engineering sometimes cannot model the behavior of geotechnical engineering piles. Most pile foundations can be modeled using Artificial Intelligence (AI) because of its capacity to foresee the intricate behavior of these structures better than conventional ways. Pile foundation design needs correct calculations of pile load capacity and settling [39]. In the past, the design of a structure's bearing capacity and settlement was done independently. In addition, since soil resistance and settlement are interconnected, the design of pile foundations must take these aspects into account. Pile load-settlement behavior must be precisely anticipated for this to work. Nevertheless, it is generally accepted that costly and time-consuming in-situ stress testing is the only way to precisely establish how pile foundations respond under loads. We can model the whole load-settlement mechanism of steel-driven piles under axial loads by applying Artificial Intelligence (AI) powered by Recurrent Neural Networks (RNN). Many in-situ full load - settlement experiments and findings from Cone Penetration Tests (CPT) are employed in calibrating and validating the constructed RNN model. RNN model can accurately estimate axially loaded steel-driven pile load-settlement behavior and may be utilized for engineering applications in everyday design processes [40].

Prediction of bearing capacity

Foundations to transport the column-load of small to moderate elevation buildings to the subsurface. The determination of soil bearing capacity, a foundation's pressure gradient may impose on the soil to meet sufficient concerns against shear failure, and acceptable total and differential settlements are examined. The least force required to destroy the supporting soil right 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 variables [2]. Engineers utilize their best judgment while completing many of these tests and computations to assess the carrying capacity of the soil. The engineer must decide where to begin and terminate the measurement to calculate the effective length. An engineer can decide to utilize the pile depth as one strategy, after which they will deduct any damaged underlying soils or combinations of soils [41]. Geotechnical Engineers may alternatively quantify it as the height of a single pile component in a particular layer of earth comprising multiple layers. Two important variables influence foundation design: bearing capacity and settling. Predicting how much weight the foundation can sustain is a crucial problem for pile foundations and has been explored by many AI researchers, particularly those employing neural networks. For instance, reported a neural network method to evaluate the frictional performance of dirt piles, which was analyzed using fieldwork data from reliable case records [42]. 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 performed between the neural network model's conclusions and those produced using the approach. Coefficients of correlation and error rates between anticipated and measured bearing capacity capacities were applied as performance metrics. Existing approaches are inferior to ANN models. The maximum load capacity of pile foundations in non-cohesive soils was predicted to employ another neural network model created shortly after. Tests on piles composed of wood, pre-cast steel, and concrete pressed into fine sand gave the evidence for this report's results. Hammer force, impact and design, pile height, load, cross-sectional diameter, stiffness, and elastic modulus were more significant elements to the ANN model [43]. The capability of the pile to support loads was the outcome of running the model. 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 vital in structural weights is necessary to study pile sets and hammer weights and types. As opposed to traditional backpropagation ANN, Bayesian ANNs provide a probability distribution across the anticipated value rather than simply one prediction. This distribution can provide information on the typical forecast error stemming from the uncertainty inherent in extrapolating noisy data. It also makes it feasible to measure the degree of confidence in a specific projection [44].

Significance to the World

Artificial Intelligence (AI) can be successfully applied across the globe in numerous applications within geotechnical engineering, especially in areas like predictions and risk assessment. The application of AI in geotechnical engineering is vital for the design, maintenance, and management of civil infrastructure projects globally. Innovations in AI, such as robotics, augmented reality (AR), and virtual reality (VR), are becoming increasingly beneficial for geotechnical projects, particularly in the construction of pile foundations and the evaluation of bearing capacity of soils [2]. This incorporation of AI will help enhance the reputation of geotechnical engineering as a critical component of civil engineering, encouraging more persons to pursue careers in this discipline. AI innovation plays a vital role in automating different areas of both civil and geotechnical engineering. Common uses include estimating concrete compressive strength, modulus of soil rupture, building pre-costs and timeframes, predictive maintenance, deformation identification, and even activities like pothole identification. Regardless of whether a country is in the early phases of development or is well-established, the construction sector can act as a significant driver of economic progress. The efficiency, prices, and quality associated with infrastructure projects are significant variables that drive the growth of this industry [45]. By employing AI to forecast critical pre-construction outputs, such as process performance, expenditures, and project execution, stakeholders can greatly enhance project efficiency and accuracy. Given the common challenges in construction, including cost overruns, delays, and structural failures, AI-driven forecasts of critical parameters like budget, durability, and the nature of the soil used in construction can help prevent these frequent issues, ensuring better outcomes for projects worldwide [46].

Future in the world

The application of Artificial Intelligence (AI) will surely simplify living worldwide in the future, potentially inspiring individuals to expand the variety and depth of their skill sets. As AI technology progresses, the tasks of builders, engineers, and architects are becoming increasingly efficient and streamlined. The growth in AI will also lead to the creation of new career possibilities, as more engineers will be needed to conduct research, create, and test AI systems. These improvements present a tremendous opportunity for the global engineering community to exhibit its ingenuity in AI development while contributing to the system's overall growth and efficiency [47]. For example, developing and maintaining well-designed infrastructure, such as roads, plays a significant role in providing a safe and efficient transportation system. Before commencing road building, numerous aspects need to be addressed, such as cost, time, labor, and the type of materials to be used. With the use of AI and computer vision techniques, these early computations for road construction can be automatically generated with minimal human intervention, especially in the era of machine learning. The use of AI in determining parameters not only decreases the time and expense involved but also enhances the accuracy of the computations by removing human errors [48].

Conclusion

This research attempted to investigate the usage of artificial intelligence applications, modeling, and prospects in geotechnical engineering was assessed in this paper. The use of artificial intelligence and the models it develops may also be observed in the world of architecture. Creating sophisticated, powerful, and visually beautiful buildings sometimes requires for a great degree of accuracy and skill to be applied in construction jobs. Any error 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 employed in the performance of numerous activities in construction and geotechnical engineering, particularly those that necessitate a high level of accuracy and precision. When it comes to civil and geotechnical engineering, there is a wide range of opportunities and difficulties that are significantly affected by many unpredictable variables that not only demand mathematical, mechanical, and physics understanding but also the competence of the specialists. The conventional operating procedures are ineffective for handling these challenges and difficulties. However, applying AI to address these complex tasks is rather basic.

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