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Application of Artificial Intelligence in Geotechnical Engineering: A Literature Review on Advances, Challenges, and Opportunities

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ABSTRACT: This paper presents a systematic literature review on the application of Artificial Intelligence (AI) in geotechnical engineering, emphasizing recent advances, persisting challenges, and emerging opportunities. The study employed a structured search in the Web of Science database, focusing on open-access journal articles and reviews published between 2020 and 2024, and included an analysis of the most cited studies from the last 15 as well as from the last 5 years. Applications identified span soil classification, slope stability assessment, shear strength estimation, settlement and bearing capacity prediction, compaction parameter estimation, and advanced computational modeling. The most frequently used techniques include Artificial Neural Networks (ANNs), hybrid evolutionary algorithms such as Harris Hawks Optimization (HHO) and Grey Wolf Optimizer (GWO), and self-organizing approaches like Group Method of Data Handling (GMDH). These methods have shown strong potential to improve predictive accuracy, reduce dependence on extensive empirical testing, and integrate complex multi-source datasets. Emerging trends point to the integration of AI with physics-based models for greater interpretability, the adoption of explainable AI (XAI) for transparency in decision-making, and the use of transfer learning to generalize models across different geotechnical contexts. Despite these advances, key gaps persist: limited uncertainty quantification, scarce field validation, and underutilization of unstructured data such as sensor measurements and borehole imagery. From a practical standpoint, AI can enhance design efficiency, optimize resource allocation, and improve safety margins in geotechnical projects through real-time monitoring and predictive modeling. Achieving this potential requires standardized protocols for model development, robust validation strategies, and stronger collaboration between academia, industry, and regulatory bodies to ensure reliable and scalable implementation. This review consolidates current knowledge, highlights methodological trends, and outlines future research priorities, contributing to the advancement of safe, efficient, and innovative AI applications in geotechnical engineering.

KEYWORDS: Artificial intelligence, geotechnical engineering, literature review, hybrid models, computational modeling.

1 INTRODUCTION

Geotechnical engineering, a discipline intrinsic to the construction of robust and safe civil infrastructure, is often challenged by the complex behavior of soils and rocks. Traditional approaches, which frequently depend on expensive and time-consuming experimental tests, as well as the inherent uncertainty of geological variability and the complex behavior of materials, have driven the search for more efficient and precise methodologies. In this context, the integration of artificial intelligence (AI) into geotechnical engineering represents a significant advance, addressing challenges inherent to a discipline fundamental to global civil infrastructure. The growing availability of geotechnical data, combined with the pressing need to optimize analysis and decision-making processes, has driven the adoption of AI as a complementary or alternative tool to conventional methods. This transformation aims to improve the accuracy, efficiency, and safety of geotechnical practices.

Baghbani et al (2022) also state that AI methods have been developed and used by a growing number of researchers in the field of geotechnical engineering over the past three decades. These methods have been considered successful due to their ability to predict complex nonlinear relationships.

AI is one of the most important technologies of the 21st century, with a profound impact on human life by changing how we work, communicate, and even influencing decision-making. Essentially, AI is a field of computer science that develops systems capable of simulating human cognitive functions, such as learning. This allows machines to interpret data and adapt to varied contexts, performing tasks autonomously without the need for direct instructions.

AI gained formal recognition as a field of study in the 1950s, more precisely in 1956, when scientist John McCarthy, in collaboration with other scholars, held a scientific meeting in the United States to debate the future of computing, dedicated to artificial intelligence and its potential impact on different areas of knowledge. This event is considered an official starting point for the field, as it introduced the idea that machines could imitate human behavior. On that occasion, McCarthy also identified different areas of study in artificial intelligence, such as neural networks ((McCarthy et al. 1956, apud Monteiro et al. 2020)). Since then, the technology has evolved significantly and is currently in a phase of rapid expansion, being widely applied by organizations in the most diverse sectors, ranging from the entertainment industry to the advanced analysis of large volumes of data. AI encompasses a variety of subfields, among which its application in the field of Geotechnics stands out in this work.

To this end, the Web of Science database was selected as the main source due to its recognized comprehensiveness and rigorous indexing criteria, especially in engineering fields. Publications between 2020 and 2024 addressing the application of AI in geotechnical engineering were analyzed through a structured search in fields such as title, abstract, and keywords. This survey aims to synthesize the current state of knowledge and identify emerging trends, emphasizing that the effective incorporation of AI in this domain requires a strategic articulation between academia and the productive sector to ensure its safe and robust implementation.

2 BIBLIOGRAPHIC REVIEW

2.1 *Artificial Intelligence and Geotechnical Engineering*

From a conceptual point of view, AI is a branch of computer science that aims to develop systems capable of simulating human cognitive functions such as perception, learning, pattern recognition, decision-making, and problem-solving (Russell & Norvig, 2021). In other words, AI allows machines to imitate human intelligence by analyzing and interpreting large volumes of data, adapting to different contexts without depending on explicit instructions for each task.

One of the classic definitions of AI points to the creation of intelligent computational systems with the ability to perform tasks autonomously, without the need for direct guidance from a human (McCarthy *et al*, 1956, apud Monteiro *et al*, 2020). Robots are representative examples of this technology: although they follow programmed instructions, many are designed to make their own decisions based on variable data and environments, characterizing behavior aligned with the concept of artificial intelligence (Lobo, 2018, apud Filho *et al*, 2022).

The importance of AI lies in its transformative potential, being applied to virtually all areas of research and work. Its application is exemplified in the medical, industrial, and financial sectors, as well as in graphic design and engineering, among others.

Especially in geotechnical engineering, a branch of Civil Engineering dedicated to studying the behavior of soils and and rocks in relation to construction projects and works, the importance of AI stands out for its ability to simplify complex processes by integrating qualitative and quantitative data.

Among the most relevant techniques, Artificial Neural Networks (ANNs) stand out for their ability to learn from data and generalize to new situations. They consist of computational models inspired by the structure and function of the human brain. They approximate complex functions through layers of units (neurons) that perform linear combinations followed by nonlinear activation functions. In geotechnical engineering, they have been widely used for tasks such as soil classification, slope stability assessment, settlement prediction, determination of pile bearing capacity, and estimation of permeability, compressibility, and compaction parameters (Chao et al. 2018; Kumar et al. 2011; Jeremiah et al. 2021; Fattah et al. 2019; Shahin et al. 2001). The applicability of ANNs is due to their ability to handle incomplete and noisy datasets and to find solutions for problems without an explicit mathematical formulation (Fattah et al. 2019).

The importance of ANNs in geotechnics lies in their ability to model highly nonlinear behavioral systems with high computational efficiency. ANN-based models, for example, have shown excellent performance in predicting the compression indices of fine soils, achieving coefficients of determination (R^2) greater than 0.80, significantly reducing the need for time-consuming laboratory tests (Uzer, 2024). In studies with stabilized soils, these models presented faster and more accurate results than traditional regression methods (Jeremiah et al. 2021).

Despite the advantages, ANNs also have limitations. One of the main criticisms is their "black box" nature, which makes it difficult to interpret internal processes and provide a physical explanation for the results obtained (Shahin et al. 2001). Furthermore, their ability to extrapolate outside the domain of the training data is limited, which can compromise predictions under extreme conditions, such as liquefaction events or atypical loads (Fattah et al. 2019). Another observed limitation is the lack of attention to quantifying uncertainties in predictions, a critical aspect in engineering (Chao et al. 2018).

Among the hybrid evolutionary methods, Grey Wolf Optimization (GWO), proposed by Mirjalili et al. (2014), stands out. It is an optimization algorithm inspired by the social hierarchy and hunting behavior of gray wolves (alpha, beta, delta, omega). It has proven effective in exploring and intensifying searches in complex solution spaces, and has been employed in engineering problems involving the optimization of multiple parameters (Mirjalili et al. 2014; Gupta & Deep, 2019; Saremi et al. 2014; El-kenawy et al. 2020). In geotechnical engineering, GWO has been used to calibrate predictive models, including those based on ANNs, providing greater accuracy and stability in the results.

Another relevant method is Harris Hawks Optimization (HHO), proposed by Heidari et al. (2019), which is inspired by the cooperative hunting strategies of the red-tailed hawk. HHO is characterized by an adaptive alternation between exploration and exploitation phases, making it efficient for solving nonlinear and high-dimensional problems (Heidari et al. 2019; Zamani et al. 2020; Yousri et al. 2021; Abdollahzadeh, et al, 2021). In geotechnics, HHO has the potential to optimize parameters in predictive models, especially when integrated with ANNs, resulting in more robust solutions for problems like settlement prediction and slope stability.

Finally, the Group Method of Data Handling (GMDH), developed by Ivakhnenko (1968), is an algorithmic modeling technique that constructs self-organizing mathematical models based on available data. GMDH iteratively generates candidate models, typically polynomial, and selects the best structure using external validation criteria (Farlow, 1981; Madala & Ivakhnenko, 1994; Ivakhnenko, 1971; Schmidhuber, 2015). This approach minimizes the risk of overfitting and is particularly useful in geotechnical engineering when modeling soil properties with limited datasets, providing a balance between model accuracy and complexity.

The combination of ANNs with evolutionary algorithms like GWO or HHO, as well as with self-organizing methods like GMDH, offers hybrid solutions capable of overcoming the individual limitations of each technique. Evolutionary algorithms can optimize the weights, topologies, and hyperparameters of ANNs, while GMDH assists in the automatic selection of the optimal model structure. In geotechnical engineering, such hybrid approaches are promising for reducing experimental costs, increasing prediction accuracy, and handling incomplete or noisy data, opening up new perspectives for safer analysis and decision-making.

3 METHODOLOGY

The methodology adopted in this literature review consisted of a systematic search and analysis of scientific articles addressing the application of artificial intelligence (AI) in geotechnical engineering. The Web of Science database was used as the primary source due to its comprehensive coverage and indexing quality in engineering fields. The Table 1 presents the quality assessment criteria used.

The search strategy involved querying Topic Search (TS), which includes the article title, abstract, author keywords, and Keyword Plus®. The search string applied was: (TS=(“Artificial intelligence”)) AND TS=(“geotechnical engineering”)).

This initial search retrieved 185 documents. The following filters were sequentially applied to refine the results:

- Document type: Filtered to include only articles and review articles, reducing the set to 155 documents.
- Open access: Applied to include only open-access publications, resulting in 65 documents.
- Publication years: Limited to the last five years (2020–2024) to reflect the most recent advances, yielding 56 documents.

An initial macro analysis was conducted on the entire set of 185 documents to identify general trends, such as the annual publication distribution, main journals, and frequently addressed AI techniques. Subsequently, a focused macro analysis was performed on the 55 articles from the last five years to examine the evolution of research topics, applications, and methodologies in recent literature.

Finally, for in-depth content analysis, the three most cited articles from each of the last five years were selected, prioritizing highly impactful studies that have contributed significantly to the knowledge base of AI applications in geotechnical engineering. These articles were analyzed regarding their objectives, AI methods employed, data used, results, and identified limitations or research gaps.

This methodological approach ensured a robust understanding of the literature landscape, enabling the identification of advances, challenges, and opportunities in integrating artificial intelligence into geotechnical engineering practice.

Table 1. Quality assessment criteria

Nº	Inclusion criteria	Exclusion criteria
1	Open Access articles	Articles without available full-text access
2	Articles and Review Articles	Proceeding Paper, Editorial Material, Book Chapters, Letter and non-article document types
3	Publications indexed in Web of Science	
4	Articles containing the terms “Artificial Intelligence” and “Geotechnical Engineering” in title, abstract, author keywords	

The VOSviewer program (Perianes-Rodriguez, Waltman, and Van Eck, 2016) was used with a minimum number of occurrences of a term set to 10 and the number of terms to be selected set to 15 for visualizing clusters that reveal the connections between the most important keywords in publications from the last five years. Additionally, Python (Pandas library) was used to generate a graph of the five most frequent keywords, both for the period 2020–2024.

4 RESULTS AND DISCUSSION

4.1 *Publication Trends*

The distribution of publications per year (Figure 1), between the years 2009-2024, indicates a growing interest in AI applications in geotechnical engineering, especially from 2021 onwards, with a significant increase in 2019 (13 articles) and 2024 (50 articles). This upward trend reflects the consolidation of AI techniques as complementary tools to conventional geotechnical methods.

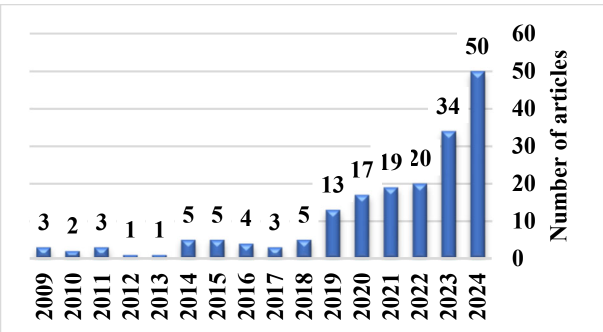

Figure 1. Trend in the number of articles on AI in geotechnical engineering over the years (2009–2024).

A macro analysis of the 56 selected articles published between 2020 and 2024 on the application of artificial intelligence (AI) in geotechnical engineering revealed important trends and research directions.

4.2 *Most Frequent Keywords*

The analysis of keywords shows that “artificial intelligence” is the dominant term, followed by “machine learning” and “artificial neural network”. These results indicate that supervised learning algorithms remain widely used in geotechnical engineering, while recent studies have also begun integrating deep learning architectures, such as artificial neural networks, to address more complex geotechnical problems (Figure 2).

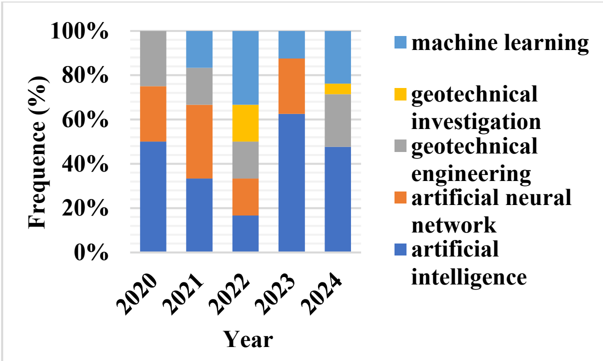

Figure 2. Dominant keywords in geotechnical engineering publications highlighting AI techniques (2020–2024).

Figure 3 shows the connections between the most important keywords in publications from the last five years. It can be observed that in the cluster containing the word “soil,” the artificial intelligence techniques with strong connections were artificial neural networks (ANN) and RMSE. Regarding the group related to AI applications in geotechnical engineering, there is a significant connection with machine learning techniques associated with the time variable.

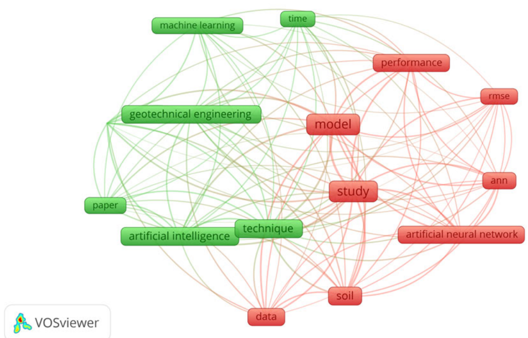

Figure 3. Keyword relationships in AI and geotechnical engineering (2020–2024).

4.3 *Highly Cited Articles (last 15 years)*

. The five most cited articles among the dataset of last 15 years (2009-2024) are:

- Emerging trends in expansive soil stabilisation: A review (266 citations). Authors: Ikeagwuani, CC & Nwonu, DC. Year: 2019.
- State-of-the-art review of some artificial intelligence applications in pile foundations (161 citations). Authors: Shahin, MA. Year: 2016.

- Predicting the settlement of geosynthetic-reinforced soil foundations using evolutionary artificial intelligence technique (130 citations). Authors: Raja, MNA & Shukla, SK. Year: 2021.
- Prediction of recompression index using GMDH-type neural network based on geotechnical soil properties (67 citations). Authors: Kordnaeij, A et al. Year: 2015.
- Predicting and validating the load-settlement behavior of large-scale geosynthetic-reinforced soil abutments using hybrid intelligent modeling (48 citations). Authors: Raja, MNA et al. Year: 2023.

The analysis of highly cited articles between 2009-2024 reveals that pile foundations, soil settlement prediction, and soil compressibility assessment are the dominant application areas for artificial intelligence in geotechnical engineering. The most prevalent AI techniques employed include artificial neural networks (ANN) and hybrid evolutionary algorithms such as Grey Wolf Optimization (GWO), Harris Hawks Optimization (HHO), and Group Method of Data Handling (GMDH). A notable trend is the integration of AI with geosynthetic reinforcement analyses and optimization algorithms, which has significantly improved the accuracy and reliability of geotechnical predictions. This reflects a paradigm shift from purely data-driven models to hybrid and metaheuristic approaches, enabling more robust modeling of complex soil–structure interaction problems in engineering practice.

4.4 *Highly Cited Articles (last 5 years)*

To better understand how Artificial Intelligence (AI) has been applied in geotechnical engineering, Table 2 summarizes recent studies (last 5 years) that employ different AI approaches across a variety of geotechnical problems. The selected works cover applications such as soil classification, slope stability, foundation behavior prediction, compaction analysis, and advanced computational modeling. The table highlights the type of AI used, the specific geotechnical domain, and the main contribution of each study, allowing for a comparative view of current research trends and methodological diversity in the field.

Figure 4 presents a horizontal bar chart illustrating the distribution of reviewed studies across different geotechnical application categories. It highlights that the highest concentration of research is found in the prediction of foundation behavior (4 studies), followed by soil compaction and density estimation (3 studies), and soil classification (2 studies). This distribution reflects a clear focus on areas with high variability and practical relevance, where AI techniques have shown strong potential for improving predictive accuracy and reducing reliance on traditional empirical methods.

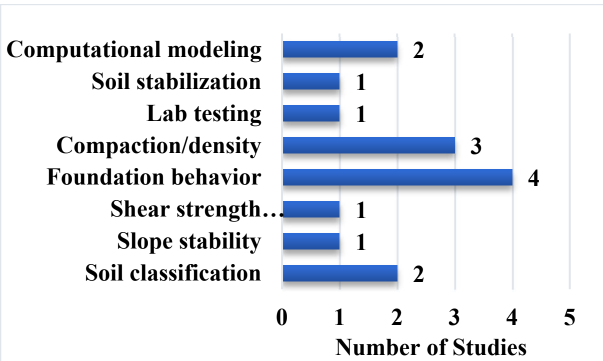

Figure 4. Distribution of studies (2020-2024) by geotechnical application category.

Table 2. Summary of AI Applications in Geotechnical Engineering

Application Category	Included Studies	AI Methods	Main Contributions
Soil classification	Sharma et al. (2021), Abdollahi et al. (2024)	Naive Bayes, KNN, Decision Tree, Random Forest, XAI	Evaluated ML algorithms and explainable AI for soil classification based on SPT data.
Slope stability	Azarafza et al. (2020)	Fuzzy Logic	Proposed a fuzzy system for landslide risk assessment in mountainous terrain.
Shear strength estimation	Cao et al. (2020)	Random Forest, SVM, Decision Tree	Compared ML models for predicting soil shear strength.
Foundation bearing capacity and settlement	Thuy-Anh Nguyen et al. (2020), Raja et al. (2021, 2023), Khan et al. (2022)	DNN, HHO + ANN, ANN + GWO, GMDH, ANFIS	Applied hybrid and neural network models for accurate prediction of settlement and bearing capacity.
In-situ density and compaction parameters	Nguyen et al. (2021), Bardhan et al. (2022, 2023)	ANN, GA-BPNN	Predicted optimum moisture content and dry density using AI models.
Laboratory geotechnical testing	Ndepete et al. (2022)	Genetic Programming	Replaced conventional lab testing with symbolic regression from AI.
Soil stabilization with industrial waste	Onyelowe et al. (2023)	ANN	Modeled behavior of stabilized expansive soils with cement kiln dust.
Geotechnical computational modeling	Liu et al. (2024), Niu et al. (2024)	Hybrid DL + Physical Modeling, Meta-learning, Transfer Learning	Developed robust hybrid models for complex or out-of-range geotechnical simulations.

Table 2 reveals that Artificial Intelligence (AI) is being applied transversally across geotechnical engineering, covering everything from classical problems such as soil classification and slope stability analysis to more advanced topics like computational modeling and tunnel behavior prediction. The most common application areas are:

- Soil classification and compaction parameters, due to their reliance on large empirical datasets.
- Foundation bearing capacity and settlement, which exhibit high variability and are traditionally difficult to predict with deterministic models.

This diversity indicates a clear maturation in the use of AI in geotechnics, reflecting the field's progression toward more complex problems.

Artificial Neural Networks (ANNs) are the most frequently used technique, appearing in at least 6 out of the 15 studies. This reflects:

- The ability of ANNs to handle nonlinearities and multivariable relationships.

- The widespread availability of modeling tools and open-source libraries, which facilitates their adoption.

In addition, hybrid models have emerged—such as HHO (Harris Hawks Optimization) + ANN and ANN + GWO (Grey Wolf Optimizer)—suggesting a growing trend to combine bioinspired algorithms with neural networks to enhance predictive performance and reduce overfitting.

Some studies adopt more sophisticated approaches, such as:

- XAI with SHAP (Abdollahi et al. 2024): using explainable AI to open the "black box" of models, a crucial aspect in engineering fields that demand transparency and reliability.
- Meta-learning and Transfer Learning (Niu et al. 2024): demonstrating a step beyond standard modeling, allowing generalization to new geotechnical scenarios, such as tunnel conditions outside the training range.
- Genetic Programming (Ndepete et al. 2022): replacing laboratory tests with symbolic models, promoting cost and time efficiency.

These approaches indicate an evolution of the field toward second-generation AI, which not only predicts but also explains and generalizes.

4.5 *Advances, Challenges, and Opportunities*

The use of hybrid models, such as HHO (Harris Hawks Optimization), GWO (Grey Wolf Optimizer), and ANNs combined with evolutionary algorithms, has been recognized as both a significant advancement and a clear attempt to overcome the limitations of isolated models by aiming for greater robustness and predictive performance. Although more complex, these techniques have proven effective in handling noisy or sparse datasets.

Despite these advancements, several gaps remain, posing challenges that need to be addressed. Few studies explore the incorporation of uncertainty or probabilistic analysis, which is crucial in soils with high variability. A lack of experimental or field validation was also observed in many of the reviewed works, limiting their practical applicability. Additionally, there is a notable scarcity in the use of unstructured data (such as borehole images, sensor data, etc.), which could be integrated with deep learning techniques for richer modeling.

From this analysis, a few key emerging trends can be identified:

- Integration of AI with physical models (Liu et al. 2024): The future lies in fusing empirical knowledge, physical principles, and machine learning to create more interpretable and generalizable models.
- Explainable and interpretable AI: As AI becomes more widespread in critical geotechnical projects (such as foundations and tunnels), transparency and understandability become essential for real-world adoption.
- Knowledge transfer across geotechnical contexts: Through transfer learning, models trained in one context are expected to be applied in others with minimal adjustment, enhancing adaptability and reducing the need for retraining.

From a practical perspective, adopting AI-based approaches in geotechnical projects can significantly reduce design time, optimize resource allocation, and improve safety margins. For instance, integrating predictive models into real-time monitoring systems can provide early warnings for slope instabilities or excessive settlements, enabling preventive measures before critical failures occur. Moreover, AI-enhanced numerical simulations can assist contractors and consultants in rapidly evaluating alternative designs, thereby facilitating more sustainable and cost-effective infrastructure solutions. These applications suggest that AI will not only complement but also transform conventional geotechnical workflows, bridging the gap between theoretical modeling and on-site decision-making.

Future research should prioritize the development of standardized protocols for model training, validation, and uncertainty quantification to ensure reproducibility and reliability across projects. Incorporating unstructured and multi-source datasets—such as geophysical surveys, remote sensing imagery, and continuous sensor data—offers a promising avenue for more comprehensive and adaptive modeling. Furthermore, fostering collaborations between academia, industry, and governmental agencies will be essential for scaling AI solutions from laboratory experiments to full-scale field applications. Such partnerships can facilitate access to high-quality datasets, accelerate model validation under diverse geological conditions, and promote the adoption of AI in codes, standards, and technical guidelines.

5 CONCLUSIONS

The findings of this study demonstrate the growing integration of Artificial Intelligence (AI) into geotechnical engineering, particularly since 2021, with significant increases in research output and methodological diversification. The analysis of recent publications revealed that AI techniques—especially Artificial Neural Networks (ANNs) and hybrid evolutionary algorithms—are being increasingly applied to traditionally complex and variable geotechnical problems, such as foundation behavior prediction, compaction parameter estimation, and soil classification. These methods have shown promise in overcoming the limitations of deterministic and empirical models by offering greater accuracy, adaptability, and the ability to model nonlinear relationships. The emergence of second-generation AI approaches, including explainable models (e.g., SHAP), transfer learning, and symbolic regression through genetic programming, indicates a clear shift toward more interpretable, generalizable, and intelligent systems.

Despite these advancements, several challenges persist. There is a notable lack of uncertainty quantification and probabilistic modeling in most studies, despite its importance in highly variable soil conditions. Moreover, many models have not yet been validated through field data or experimental testing, which limits their applicability in real-world projects. The underutilization of unstructured data—such as sensor readings and borehole imagery—also points to an untapped opportunity for integrating deep learning and computer vision techniques. Moving forward, the integration of AI with traditional engineering models, greater emphasis on model interpretability, and the development of transferable models across geotechnical contexts will be essential to fully realize the potential of AI in advancing geotechnical engineering practice.

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