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REVIEW

A systematic review and meta-analysis of artificial neural network, machine learning, deep learning, and ensemble learning approaches in field of geotechnical engineering

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Abstract

Artificial neural networks (ANN), machine learning (ML), deep learning (DL), and ensemble learning (EL) are four outstanding approaches that enable algorithms to extract information from data and make predictions or decisions autonomously without the need for direct instructions. ANN, ML, DL, and EL models have found extensive application in predicting geotechnical and geoenvironmental parameters. This research aims to provide a comprehensive assessment of the applications of ANN, ML, DL, and EL in addressing forecasting within the field related to geotechnical engineering, including soil mechanics, foundation engineering, rock mechanics, environmental geotechnics, and transportation geotechnics. Previous studies have not collectively examined all four algorithms—ANN, ML, DL, and EL—and have not explored their advantages and disadvantages in the field of geotechnical engineering. This research aims to categorize and address this gap in the existing literature systematically. An extensive dataset of relevant research studies was gathered from the Web of Science and subjected to an analysis based on their approach, primary focus and objectives, year of publication, geographical distribution, and results. Additionally, this study included a co-occurrence keyword analysis that covered ANN, ML, DL, and EL techniques, systematic reviews, geotechnical engineering, and review articles that the data, sourced from the Scopus database through the Elsevier Journal, were then visualized using VOS Viewer for further examination. The results demonstrated that ANN is widely utilized despite the proven potential of ML, DL, and EL methods in geotechnical engineering due to the need for real-world laboratory data that civil and geotechnical engineers often encounter. However, when it comes to predicting behavior in geotechnical scenarios, EL techniques outperform all three other methods. Additionally, the techniques discussed here assist geotechnical engineering in understanding the benefits and disadvantages of ANN, ML, DL, and EL within the geo techniques area. This understanding enables geotechnical practitioners to select the most suitable techniques for creating a certainty and resilient ecosystem.

Keywords Artificial neural networks · Machine learning · Deep learning · Ensemble learning · Geotechnical engineering

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1 Introduction

Geotechnical engineering involves investigating and utilizing naturally occurring materials, including soil, rock, and intermediate geomaterials, such as coal [1, 2]. Among these materials, soil is distinguished due to its complex physical, mechanical, and chemical properties in engineering materials [3, 4]. These materials exhibit inherent anisotropic and heterogeneous characteristics resulting from various origins and formation mechanisms, presenting difficulties in understanding and forecasting [5, 6]. Traditionally, geotechnical engineers employ two primary approaches for investigating material behaviors: (1) laboratory and field tests and (2) numerical and analytical methods [7, 8]. While laboratory and field tests offer descriptive insights, they often entail substantial costs and time commitments [7, 9]. Conversely, numerical methods, like finite elements [10–12] or discrete analyses [12, 13], provide cost-effective virtual assessments of geotechnical material behavior [7, 14].

Computational intelligence and soft computing analyses have gained recognition due to the complex challenges encountered in various engineering applications. These approaches have gradually replaced the need for complex calculations [15–17]. There are numerous advantages to employing AI techniques in geotechnical engineering [18], including:

1. AI can model intricate and nonlinear processes without presuming initial input–output relationships [19, 20].
2. AI demonstrates its effectiveness in forecasting, surveillance, choice-making, recognition, and classification in various situations [21].
3. AI has the capability to provide precise predictions even when there are no established physical parameter relationships available [22].
4. AI has the ability to process extensive datasets, identify patterns, and occasionally generate missing data [23, 24].

Artificial neural networks (ANNs) can evaluate all feasible alternatives for a given project outcome using complex mathematical models and advanced software tools [25, 26]. The integration of ANNs with optimization algorithms is essential to mitigate error rates, particularly in complex scenarios like compressed sensing [27, 28]. ANN provides essential tools for geotechnical engineers in prominent consulting firms, enabling them to make quick and informed decisions, thereby improving performance and mitigating risks [29].

Geotechnical challenges are full of uncertainties and include different factors that avoid direct determination by engineers, leading to the quick adoption of machine learning (ML) techniques [30–32]. ML techniques can recognize potential correlations in data without any prior presumptions [33–36]. Additionally, deep learning (DL), a subfield of ML, aims to enhance the learning algorithms' capability to comprehend complex data. This is achieved using ANNs with multiple layers of interconnected nodes [37]. While DL has exhibited success in tackling learning challenges, its performance is influenced by various factors, and optimizing DL remains an ongoing focus of research in the field of AI [38, 39]. Furthermore, as computational efficiency advances, ongoing investigations into AI and DL are taking place [40, 41].

The primary objectives of this research are to comprehensively assess the applications of ANN, ML, DL, and EL in geotechnology forecasting and to establish a systematic categorization framework. Through the analysis of an extensive dataset, this study aims to provide insights into utilizing these techniques in addressing geotechnical challenges, enabling informed decision-making in this field. Table 1, which serves as an abbreviation table, provides crucial references to assist readers in understanding the fundamental ideas presented in the paper. Figure 1 illustrates various sections covered in this review paper.

2 Literature review

Geotechnical engineering is a multidisciplinary field that encompasses various sub-disciplines within engineering and geology [1, 8]. It involves the study of soil and rock behavior to ensure the stability, safety, and longevity of infrastructure and construction projects [8–10]. In structural engineering, it addresses foundation design and soil–structure interaction [42, 43]. Construction engineering involves ground structures, excavation, soil improvement, and earthwork [8, 44]. Environmental engineering focuses on geoenvironmental concerns, while earthquake engineering deals with seismic geotechnics and ground motions [8, 9, 45].

Mechanical engineering aspects include rock mechanics, soil mechanics, and ice mechanics [9, 46]. Geology plays a role in geological engineering, geomaterials analysis, and geohazard assessment [8, 9]. Hydraulic engineering covers earth dams, scouring, groundwater drainage, and marine geotechnics [8, 47], while transportation engineering includes tunneling and road engineering [8, 9]. Figure 2 illustrates these diverse sub-disciplines within the field of geotechnical engineering. Geotechnical engineers apply their expertise across these domains, ensuring the proper utilization of soil and rock properties in diverse construction and environmental contexts.

AI consists of a sophisticated collection of programming techniques [48, 49]. Many of these techniques are founded

Table 1 Explanations of Abbreviations Employed throughout the Paper

AI	Artificial Intelligence	DENN	Differentiated Evolution Neural Network
SVM	Support Vector Machine	GEP	Gene Expression Programming
MLP	Multiplayer Perceptron	ANFIS	Adaptive Neuro-Fuzzy Inference Systems
AE	Autoencoder	ANOVA	Analysis of Variance
GA	Genetic Algorithm	FA	Firefly algorithm
BP	Backpropagation	VI	Variational Inference
PSO	Particle Swarm Optimization	MCD	Monte Carlo Dropout
BPNN	Backpropagation-Based Neural Network	AutoNN	Autoencoder Neural Network
ANN	Artificial Neural Network	MARS	Multivariate Adaptive Regression Spline
CNN	Convolutional Neural Network	CFNN	Cascade-forward neural network
RF	Random Forest	LM	Levenberg–Marquardt
LSTM	Long Short-Term Memory	AERBF	Adaptive Ensemble of Radial Basis Functions
RNN	Recurrent Neural Network	MCS	Monte Carlo simulation
DBN	Deep Belief Network	GP	Genetic Programming
SVR	Support Vector Regression	EPR	Evolutionary Polynomial Regression
K-NN	K-Nearest Neighbors	MLR	Multiple Linear Regression
NN	Neural Networks	ICA	Imperialism Competitive Algorithm
ML	Machine Learning	PR	Penetration Rate
DL	Deep Learning	TBMs	Tunnel Boring Machines
DTL	Deep Transfer Learning	UCS	Unconfined Compressive Strength
RMSE	Root Mean Squared Error	OPF	Original performance function
EPA	Ensemble Predicting Algorithm	HSDA	High-Strength Deformed Alloy
CatBoost	Categorical Boosting	VE	Voting Ensembles
XGBoost	Extreme Gradient Boosting	SE	Stacking Ensembles
RBFNN	Radial Basis Function Neural Network	GBM	Gradient Boosting Machines
GRNN	Generalized Regression Neural Network	BLR	Bayesian Linear regression
DT	Decision trees	REG	Least Square Linear Regressor
MPS	Multiple Point Statistics	NB	Naive Bayes
BCS	Bayesian Compressive Sensing	PCA	Principal Component Analysis
BN	Bayesian network	FL	Fuzzy logic
BR	Bayesian regularization	DJ	Decision jungle
SCG	Scaled conjugate gradient	PCA	Principal Component Analysis
JS	Jellyfish Search	FRS	Fiber-Reinforced Soil
WFLSSVR	Weighted-Feature Least Squares Support Vector Regression	RMR	Rock Mass Rating
VP	P-wave velocity	NGL	Next Generation Liquefaction
CPT	Cone Penetration Test	CEC	Cation Exchange Capacity
BRT	Boosted Regression Tree	BDT	Boosted Decision Tree
GES	Gully Erosion Susceptibility	RDF	Random Decision Forest
SRM	Statistical Risk Minimization	Cc	coefficient of curvature
LSSVM	Least Squares Support Vector Machines	ML	Multivariate Regression
TCN	Temporal Convolutional Network	SAEs	Stacked Autoencoders
RFR	Random Forest Regression	DTR	Decision Tree Regression
MARS	Multivariate Adaptive Regression Splines	LR	Logistic Regression
FFNN	Feed Forward Neural Network	FOS	Fiber Optic Sensors
MEM	Micro-Electro-Mechanical	DM	Deep Mixing
EHO	Elephant Herding Optimization	WDO	Wind-Driven Optimization
SFLA	Shuffled Frog Leaping Algorithm	GWO	Grey Wolf Optimizer
SSA	Salp Swarm Algorithm	BBO	Biogeography-Based Optimization
SSS	Soil Shear Strength	FEM	Finite Element Method

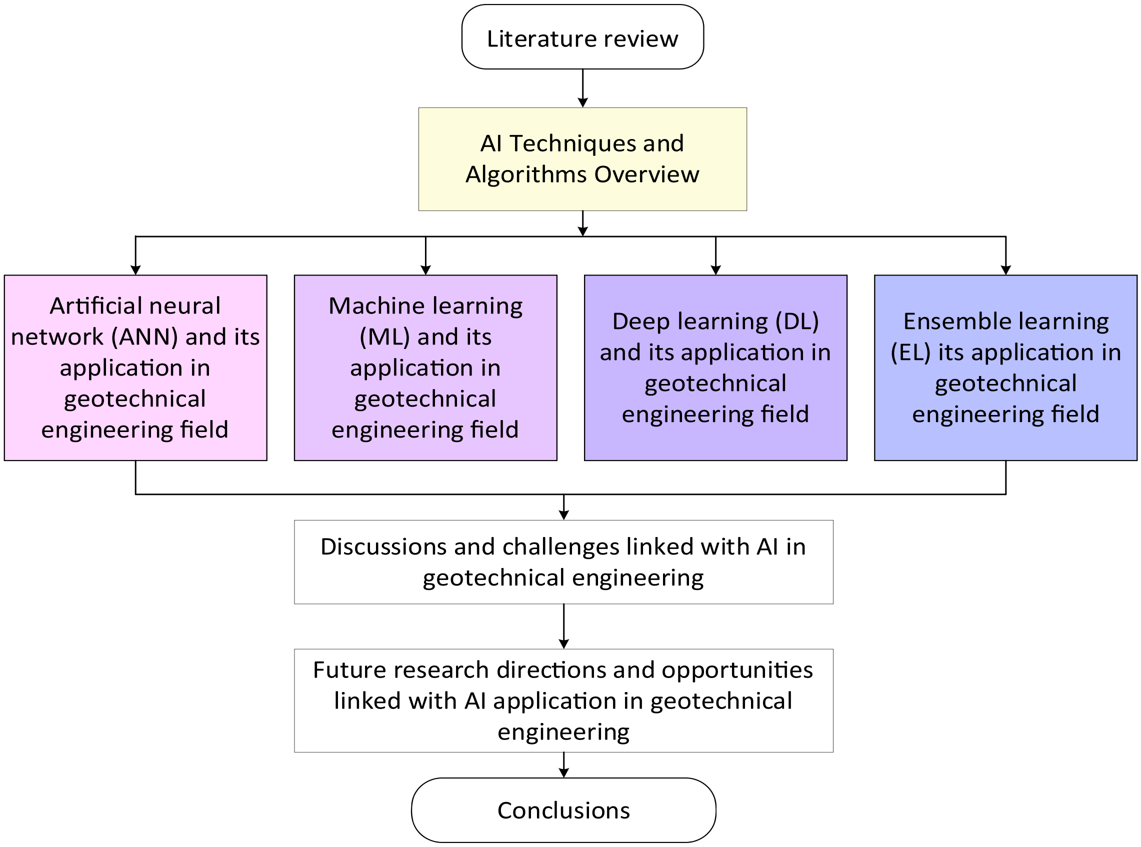

Fig. 1 Outline of various sections covered in the current review paper

on the idea that knowledge gaining, organization, access, and modification, in both humans and machines, form the basis for 'intelligent' decision-making [50–54]. AI techniques find application in a wide array of geographical issues, including modeling individual and collective decision-making and developing expert and 'intelligent' geographical information systems [55]. Geotechnical engineers employ various AI techniques to solve diverse challenges [56]. Adopting AI applications in geotechnical engineering has revolutionized the resources available to industry experts, providing them with advanced tools for in-depth data analysis and intricate modeling [57, 58] decision-making [59]. Recent instances of GeoAI endeavors involve the identification of terrain features [60, 61], the detection of densely distributed building footprints [62–64], the extraction of information from scanned historical maps [65–67], and semantic classification, such as with LiDAR point clouds [68–70], novel methods for spatial interpolation [71], and advances in traffic forecasting [72–74]. Integrating AI applications in this field enhances the analytical capabilities of industry professionals and fundamentally alters their decision-making processes [75–79]. Through precise data analysis and the application of dynamic modeling, AI enables professionals to optimize site selection, fine-tune design specifications, and adeptly anticipate and manage risks, ultimately leading to the successful and sustainable execution of geotechnical projects [80]. AI plays a pivotal role in advancing sustainable construction and infrastructure projects by efficiently allocating resources, reducing environmental impacts, and optimizing material usage, energy consumption, and waste management techniques in geotechnical engineering [81–83]. It is a powerful tool in sustainable construction, effectively managing resources to minimize environmental impacts [84–87]. By optimizing material distribution and utilization, reducing energy consumption, and limiting waste, AI not only results in cost savings but also significantly diminishes the ecological footprint in construction [88–90]. Furthermore, AI can also be utilized to enhance other critical factors, such as mechanical strength and bearing capacity [91, 92]. This comprehensive approach utilizes AI's capabilities to address a broader spectrum of considerations in construction, resulting in improved sustainability and performance. Nevertheless, the integration of AI in geotechnical engineering faces challenges, mainly due to the necessity for comprehensive and reliable data, particularly in specialized or remote projects [18, 93–95]. Ensuring data quality is essential, emphasizing

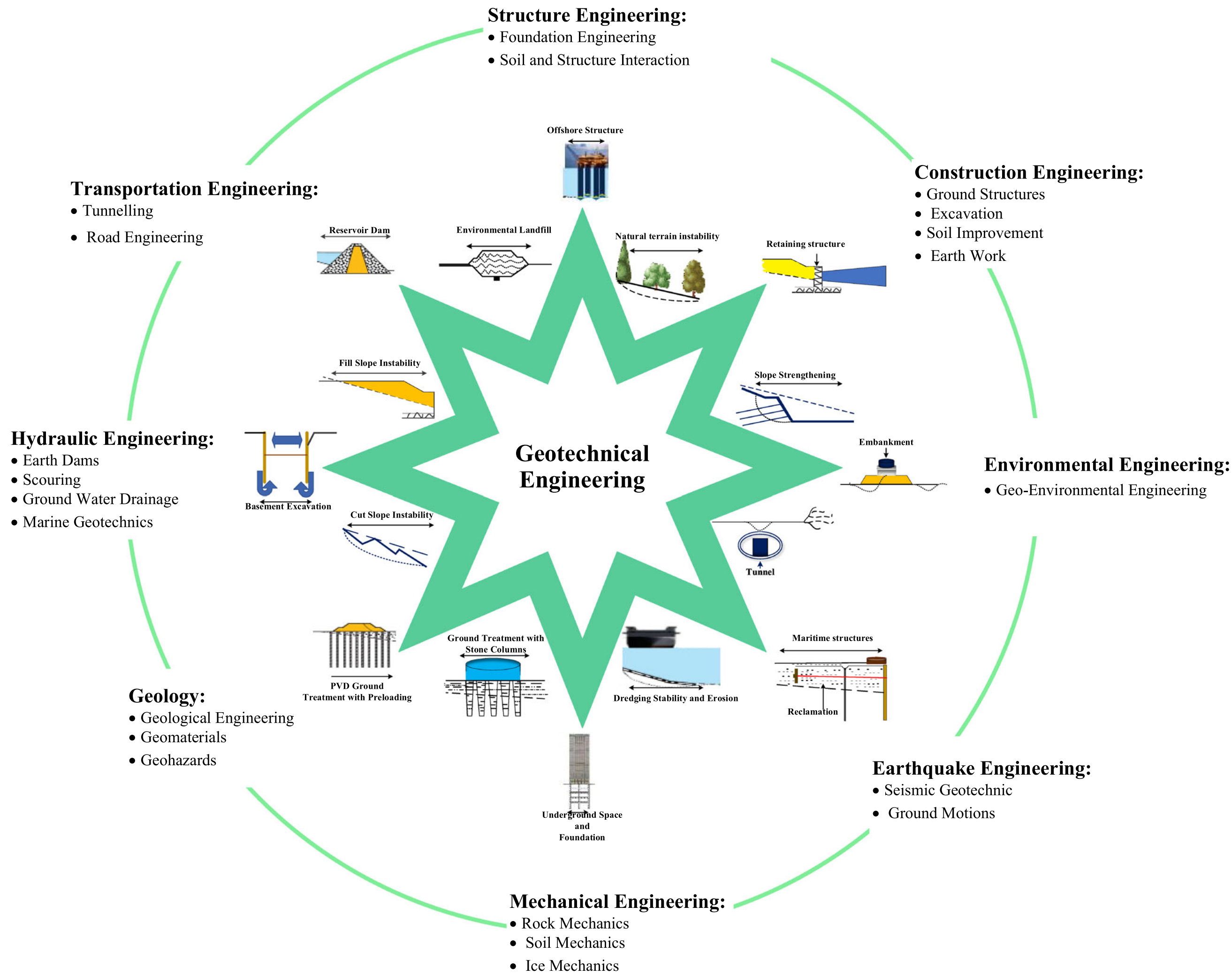

Fig. 2 Overview of geotechnical engineering sub-disciplines

Table 2 Review articles using AI techniques in geotechnical engineering

AI technique	[8]	[99]	[100]	[101]	[102]	[103]	[104]	[105]	[106]	This paper
ANN	✔	✔	✔	✗	✔	✔	✔	✗	✔	✔
ML	✗	✗	✗	✔	✗	✗	✗	✗	✔	✔
DL	✗	✗	✗	✗	✗	✗	✗	✔	✗	✔
EL	✗	✗	✔	✔	✗	✗	✗	✗	✗	✔

the significance of a balanced approach in developing and validating AI models [96–98]. Table 2 discusses some review articles by researchers using AI in geotechnical engineering from 2017 onwards. Also, these reviews have concentrated on one or two AI techniques. In contrast, this review article offers a comprehensive exploration of all four AI techniques (ANN, DL, ML, and EL) within the field of geotechnical engineering. The study showed a co-occurrence keyword analysis encompassing AI techniques (ANN, DL, ML, and EL), systematic review, geotechnical engineering, and review; the data were gathered from the Scopus database and then visualized utilizing VOS Viewer. The dimensions and annotations of each circle represent the importance of the corresponding keyword. Lines connecting them represent connections between these keywords. Various colors signify separate clusters, each associated with its own specialized domain of knowledge. Figure 3 visually represents the research trend observed from 2020 to 2023.

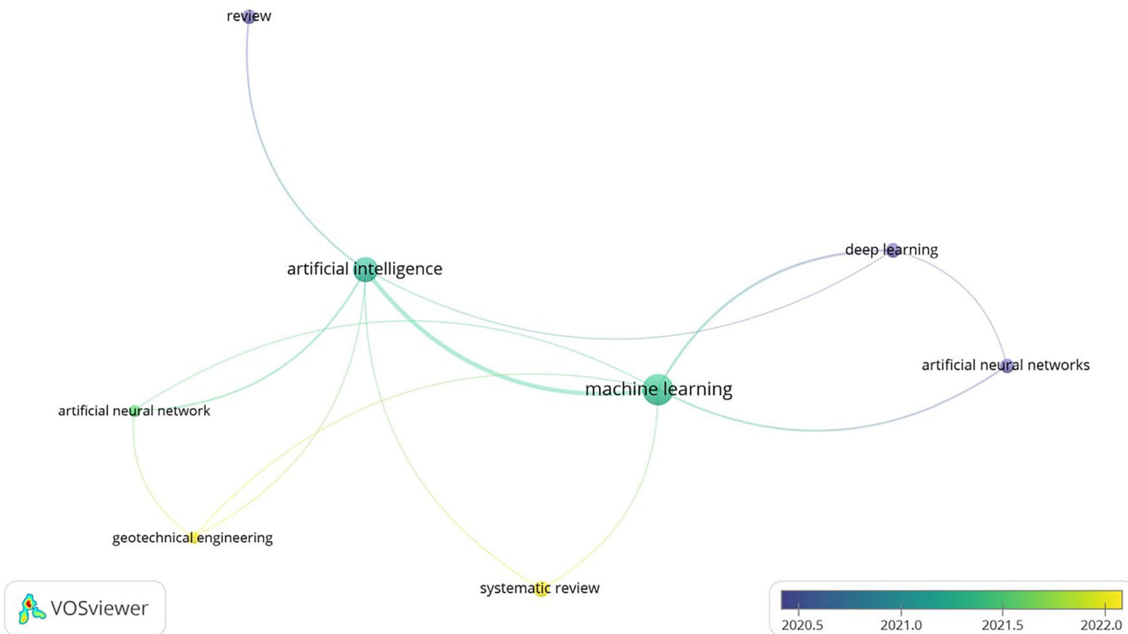

Fig. 3 Application of AI methods in review papers within the field of geotechnical engineering, supported by total publications retrieved from the Scopus database

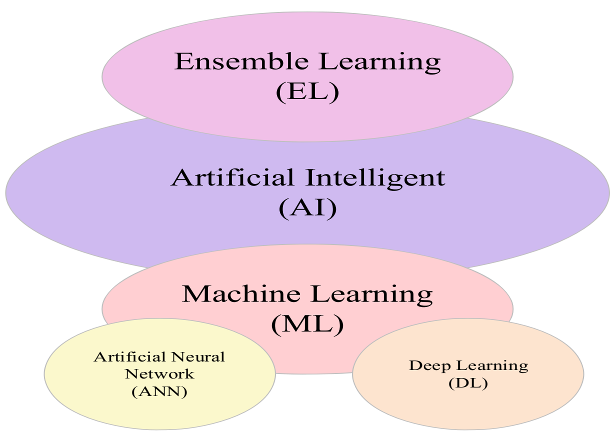

Fig. 4 Various categorizations of AI

3 AI techniques and algorithms overview

The advent of big data, cloud computing, artificial neural networks, and machine learning has empowered engineers to develop machines capable of emulating human intelligence [107, 108]. Expanding on these advancements, this research designates machines capable of perceiving, recognizing, learning, reacting, and problem-solving as AI [109–111]. This inevitably signifies a transformative influence on future workplaces, as AI has the potential to enhance human performance to higher standards [112–114]. Consequently, it is poised to emerge as the next groundbreaking innovation [115]. AI is classified into four distinct approaches, including artificial neural networks

Table 3 Comparing the advantages and disadvantages of ANN, ML, DL, and EL

Aspect	ANN [116]	ML [117]	DL [118]	EL [119]
Complexity	Moderate	Moderate	High	Moderate to high
Data requirement	Moderate	Small to moderate	High	Moderate to high
Interpretability	Low	High	Low	Moderate to high
Performance	Task-dependent, moderate to high	Task-dependent, moderate to high	State-of-the-art in some tasks	Improved performance
Applications	Various	Versatile	Dominant in specific domains	Diverse
Overfitting	Prone with complexity	Prone with complexity	Prone with insufficient data	Mitigated with ensemble

Table 4 Using ANNs Techniques in Geotechnical Engineering

Ref	Focus	Geotechnical classification	Technique	Aim	Result
[175]	The research forecasts the cohesion of sandy soil reinforced with fibers	Soil improvement—soil reinforcement	GA-ANN + PSO -ANN	The research assesses how factors such as fiber percentage, fiber length, deviator stress, and pore water pressure influence cohesion values	The research successfully created and assessed two hybrid models based on ANNs. The GA-ANN model exhibited superior predictive accuracy for cohesion values in fiber-reinforced sandy soil
[176]	The study develops a highly accurate prediction model for the PR of TBMs in geotechnical engineering applications	Tunnel engineering	FA + ANN	The main objective of this study was to create a precise predictive model for estimating TBM penetration rates. This endeavor sought to mitigate risks linked with tunneling projects and elevate prediction accuracy by applying the hybrid model (FA-ANN)	The research showcases that the FA-ANN outperforms conventional ANN models in addressing geotechnical engineering issues. Additionally, it identified RPM as the most influential parameter for accurately predicting penetration rates
[177]	The study constructed a precise predictive model for UCS in cement-stabilized sandy soil	Soil improvement—soil stabilization	ANN	The research sought to identify the pivotal factors influencing UCS and provide practical equations for accurately estimating UCS in real-world scenarios. Illustrate the efficacy of the ANN technique in forecasting geotechnical parameters	The study showcased that the devised ANN-based model accurately forecasted UCS values, displaying a strong correlation coefficient and minimal root mean squared errors. Additionally, it underscored the substantial impact of cement content and the proportion of soil particles passing through a 0.5 mm sieve on the UCS of stabilized soil
[178]	The research focuses on forecasting rocks' Uniaxial Compressive Strength (UCS) within geotechnical engineering. It explores the utilization of BNNs in this field, specifically in predicting soil properties like the compression index (Cc) and undrained shear strength (su) of clays	Rock engineering—rock mechanics—strength	BNNs + VI + MCD	The connection between input parameters and soil characteristics by using models based on BNNs	This research illustrates the efficiency of BNNs in identifying patterns and providing precise forecasts for Cc and su, especially when dealing with abundant data. Nevertheless, their predictive accuracy may require enhancement when working with limited datasets. Despite this limitation, BNNs exhibit considerable potential for geotechnical design due to their robust predictive capabilities and reliable assessment

Table 4 (continued)

Ref	Focus	Geotechnical classification	Technique	Aim	Result
[179]	This study is centered around creating and assessing an intelligent prediction model designed to estimate the UCS of fragmented rocks within the field of geomechanics	Rock engineering—rock mechanics—strength	AutoNN + MARS + Standalone AI benchmark models such as BPNN + GRNN + RBFNN + RF	This study provides geotechnical, civil, and mining engineers with a valuable tool for accurately predicting UCS in various engineering applications	The study finds that the hybrid AutoNN-MARS model surpasses other AI models in geotechnical engineering, specifically in predicting the UCS of rocks. This model demonstrates exceptional precision with a correlation coefficient (r) of 0.99999, along with the lowest errors recorded (RMSE = 0.39453 and Pi = 0.31406)
[180]	This study precisely predicts the swelling potential of clayey soils, a critical factor in evaluating the enduring stability of structures and foundations in geotechnical projects	Soil mechanics—swelling soil	FFNN + CFNN + LM + Bayesian optimization algorithm	The study is to furnish geotechnical engineers with a dependable tool for assessing and mitigating the challenges of swelling in clay soils during construction and foundation projects	The research reveals that the FFNN model, trained using the Levenberg–Marquardt algorithm, effectively predicts clay swelling potential. It outperforms current practical methods, demonstrating its reliability in geotechnical projects under various soil conditions
[181]	This study enhances the computational efficiency of geotechnical reliability analysis, particularly in cases were assessing the OPF of geotechnical structures proves time-consuming	Geotechnical reliability analysis	AERBF + MCS + Active learning function	The study aims to tackle the difficulties of choosing a suitable surrogate model and mitigating the computational cost of training these models	The AERBF ensemble model serves as a substitute for the OPF in geotechnical structures, enhancing computational efficiency through intelligent, active learning
[182]	This study involves developing and implementing an ANN model to accurately identify dispersive soils in civil and hydraulic engineering projects	Soil mechanics—dispersive clay	ANN	The study was to address the crucial issue of accurately identifying the dispersibility of soils. When subjected to seepage or surface erosion, dispersive soils can result in structural damage or even accidents in civil and hydraulic engineering projects	The study showcased the effective use of an ANN model, which was created using the TensorFlow library in Python. This model accurately identified dispersive soils and was trained using data from 11 water conservancy projects. The results demonstrated its high effectiveness in predicting soil dispersibility
[170]	The study used artificial intelligence-based techniques to create predictive models for different properties of black cotton soil treated with HSDA	Soil improvement—soil stabilization	ANN + GP + EPR	The study provides a technique for sustainable subgrade construction by utilizing materials derived from waste sources	The methodology forecast parameters, including bulk density, linear and volumetric shrinkages, and desiccation cracking of black cotton soil treated with HSDA. The research process entailed the characterization and classification of the soil, the production of HSDA from sawdust ash, and its application to treat the soil at varying percentages

Table 4 (continued)

Ref	Focus	Geotechnical classification	Technique	Aim	Result
[183]	The study predicts hydraulic conductivity in soils, emphasizing the challenges of soil heterogeneity and the extensive variability of hydraulic conductivity values among various soil types	Soil mechanics—hydraulic conductivity	ANN + MLR	The study develops precise predictive models for soil hydraulic conductivity using easily accessible soil properties. Additionally, it seeks to assess and compare the performance of ANN and MLR in this prediction	The findings indicate that the ANN model surpasses MLR, displaying greater accuracy in predicting hydraulic conductivity
[184]	This study forecasts the permeability of dispersive soils that have undergone treatment with lime and pozzolan	Soil mechanics—dispersive clay—permeability—soil improvement	ANN + MLP	This study constructs a predictive model for permeability in dispersive soils after treatment with lime and pozzolan. The purpose is to establish a time-efficient and economically feasible method	The study utilizes ANN modeling to expedite and enhance the precision of permeability determination. The selected neural network model, a multilayer perceptron with nine nodes in the hidden layer, produced a remarkably high coefficient of determination (R^2) of 0.9895 and a very low RMSE of 3.5604 × 10^-8 cm/sec
[185]	This study develops intelligent models to forecast the bearing capacity of driven piles in cohesionless soil	Foundation engineering-pile-bearing capacity	ANN + ANFIS + ICA	This study provides precise predictions that can assist in the initial design phase of geotechnical structures	The models utilize parameters, including internal friction angle, effective vertical stress, pile area, and pile length, as input variables to predict the total bearing capacity of driven piles. Notably, among these models, the ANFIS model demonstrated superior performance in accurately forecasting the bearing capacity of the piles
[186]	The research focuses on the rapid safety assessment of a foundation ditch throughout the construction	Foundation engineering	GA-BP		
	The research emphasizes the use of various sensing technologies, such as distributed FOS and MEM sensors, for the purpose of monitoring factors like settlement, horizontal displacement, and axial force within the foundation ditch	The research shows that all four ANN techniques are successful in forecasting alterations in settlement, horizontal displacement, and axial force, with minor inaccuracies (below 5%). Among these approaches, the GA-BP neural network is recognized as the most proficient for predictive analysis			

Table 4 (continued)

Ref	Focus	Geotechnical classification	Technique	Aim	Result
[187]	The research focuses on the DM technique, particularly the application of floating soil–cement columns for enhancing soil quality	Soil improvement	ANFIS	The objective is to examine the bearing capacity of these columns and create a forecasting model for cohesive soft soils reinforced with soil–cement columns using ANFIS	The physical modeling experiments illustrate that the introduction of soil–cement columns resulted in a significant enhancement of bearing capacity, ranging between 29 and 79%. The ANFIS predictive model displayed impressive coefficients of determination (R2) of 0.989 for the training dataset and 0.960 for the testing dataset, indicating its effectiveness in forecasting bearing capacity
[188]	The research focuses on accurately determining SSS, a critical parameter in civil engineering projects	Soil mechanics—shear strength	EHO + SFLA + MLP + SSA + WDO + ANN	The objective of the described study is to create innovative, intelligent models for predicting SSS	The research assesses the effectiveness of the suggested models using metrics like Error and Correlation. Among these models, SSA-MLP is singled out as the most effective prediction technique, followed by WDO-MLP, SFLA-MLP, and EHO-MLP. This means that the SSA-MLP model can serve as a dependable alternative to conventional methods for predicting soil shear strength
[189]	The objective of the study outlined to create innovative hybrid intelligent models for estimating landslide susceptibility	Landslide susceptibility	ANFIS + GWO + BBO	The goal is to supply a robust and precise tool for modeling landslide susceptibility, one that can be adapted and used by modelers according to their particular situations and needs	Both ANFIS-BBO and ANFIS-GWO models demonstrated excellent fit accuracy and predictive capability, with a notable distinction in performance shown by the Wilcoxon signed-rank test, ultimately yielding high-quality outcomes
[190]	This research uses ANN to develop a reliable method to predict the deflection of laterally loaded piles placed near a slope	Foundation engineering— pile deflection	FEM + ANN	Developing an ANN model for predicting pile deflection near slopes offers a cost-effective alternative to complex and expensive FEM simulations	The developed ANN model demonstrates exceptional accuracy with minimal errors ($R^2 = 0.9647$) when applied to rigid piles in cohesionless soils. While the study acknowledges certain limitations, it recommends the integration of additional parameters to enhance the comprehensiveness of the model

Table 4 (continued)

Ref	Focus	Geotechnical classification	Technique	Aim	Result
[191]	This study explores the comparative analysis of two methods for predicting the shear strength of soil reinforced with fibers. The first method under scrutiny is the Gray and Ohashi (GO) model, an established analytical framework for reinforced soil. Additionally, the authors introduce and assess an ANN model specifically designed for this purpose. By comparing these approaches, the research aims to discern the efficacy and potential advantages of employing ANN models over established analytical methods like GO in predicting shear strength	Soil improvement—soil reinforcement	ANN	The study investigates the influence of fiber length, proportion, and orientation on shear strength. Furthermore, it seeks to evaluate and compare the predictive accuracy of both the GO model and ANN model in determining the shear strength of reinforced soil	Fiber reinforcement significantly improves shear strength, with the effect depending on length, proportion, and direction. An ANN model, developed and trained based on experimental data, showed higher accuracy (lower errors, $R^2 = 0.960$) than the GO model. Unlike the GO model, which necessitates multiple equations and overlooks fiber failure, the ANN model integrates all pertinent influencing factors into a single equation, offering a more comprehensive predictive framework

(ANN), machine learning (ML), deep learning (DL), and ensemble learning (EL). The categorization of these methods is depicted in Fig. 4. Furthermore, for clarity, Table 3 offers a comprehensive comparison of these techniques across various dimensions. As demonstrated in Table 3, the assessment of complexity, data requirements, and interpretability can vary depending on the specific architecture and algorithm. These characteristics can be influenced by factors such as data quality and domain expertise.

3.1 Artificial neural network (ANN) and its application in geotechnical engineering field

The development of the ANN appeared as a solution for tackling challenges involving complex patterns and predictions [120, 121]. Inspired by the information processing mechanisms of the human brain, studies have defined the complex, multi-layered structure of ANN [122, 123]. These neural networks consist of three essential layers: the input, hidden, and output [124]. Neurons are distributed across these layers in a multilayer ANN, each neuron serving as a crucial processing unit. The initial level, represented by the input layer, acquires information to reduce errors and enhance computations [125, 126]. Consequently, the logical determination of the number of neurons is crucial. The input signal can move to subsequent layers due to the interconnectivity among neurons. Neuron weight signifies their capacity to communicate with one another; moreover, the weight and neuron count in preceding layers determine the number of neurons in each layer [127, 128]. It is worth noting that the discretion of the number of hidden layers and neurons is possible. Like other networks, ANNs serve as an exceptional modeling tool for analysis. They excel in defining nonlinear network function evaluation, pattern recognition, data classification, simulation, clustering, and optimization, all essential features of AI [129]. ANN can be categorized into six distinct network types, which include:

- *Feed Forward Neural Network (FFNN)* FFNN is a foundational framework within supervised ANNs, demonstrating notable proficiency in recognizing patterns [130]. It systematically handles information through input, hidden, and output layers linearly, devoid of feedback connections [131]. It is skilled at complex pattern learning, although it requires precise adjustment of hyperparameters to achieve the best results.
- *Back Propagation Neural Network (BPNN)* The Backpropagation Neural Network (BPNN) is a widespread ANN used in supervised learning tasks. It demonstrates proficiency in comprehending complex relationships

[132]. Functioning through interlinked layers, it refines weights using backpropagation to reduce output differences [133].

- *Radial Basis Function Neural Network (RBFNN)* The RBFNN is a neural network model designed for various ANN applications [134–136]. It utilizes radial basis functions. This architecture enables it to excel in both pattern recognition and regression tasks [137]. By employing radial basis functions, it efficiently processes data and adjusts parameters dynamically, ensuring accurate and reliable results [138, 139].
- *Bayesian Regression Neural Network (BRNN)* The BRNN combines neural networks with Bayesian regression to represent complex models [140, 141]. It utilizes neural networks to manage nonlinear patterns and employs Bayesian methods to measure uncertainty, making it advantageous for various applications [142].
- *Generalized Regression Neural Network (GRNN)* The GRNN is a sophisticated model proficient in making predictions by estimating functions through a radial basis function strategy [143, 144]. This feature makes it especially apt for efficient training and approximating smooth functions [145–147]. The GRNN, based on in radial basis functions (RBFs), is recognized for its effectiveness in regression assignments.
- *Differentiated Evolution Neural Network (DENN)* DENN is a type of ANN that uses the differential evolution algorithm to optimize its network structure and parameters. The DENN integrates advanced evolution strategies in neural network training to accelerate convergence speed, improve solution quality, and enhance generalization capabilities for complex optimization tasks [148, 149].

ANN can be employed for a range of tasks in geo-engineering, including Soil Classification [93, 150, 151] and Property Estimation [93, 152, 153], Settlement and Settlement Prediction [93, 154–156], Slope Stability Analysis [157–159], Seismic Hazard Assessment [160, 161], Groundwater Flow Modeling [162, 163], Tunneling and Excavation [164–166], Site Characterization [95, 167], Risk Assessment [168, 169], Material Behavior Modeling [170, 171], and Optimization [172, 173].

Different types of ANNs, including GRNN, DENN, BRNN, RBFNN, and FFNN, may be chosen based on the specific problem, data availability, and the desired level of complexity. For example, RBFNNs may be used for data interpolation and function approximation, while FFNNs are suitable for general regression and classification tasks. DENN, if applicable to geotechnical problems, may offer specific advantages in terms of optimization and adaptation [174].

Table 4 displays the employment of ANN techniques in geotechnical engineering.

From the information provided, it is clear that a diverse array of advanced AI techniques, including various types of neural networks and hybrid models, have been successfully utilized in research within the field of geotechnical engineering [104, 192]. These approaches have addressed various geotechnical challenges, from soil property prediction to estimating material strengths and evaluating geotechnical structure performance. The outcomes substantiate the efficacy of AI-based models in providing accurate and dependable forecasts across different facets of geotechnical engineering. Furthermore, these models offer the potential to improve computational efficiency and make valuable contributions to advancing more sustainable practices in soil stabilization and subgrade construction. [8, 100, 104, 176].

The study performed a keyword analysis, giving particular attention to the application of ANN techniques in the field of Geotechnical Engineering. The data were gathered from the Scopus database and then visualized utilizing VOS Viewer. Over the period from 2016 to 2023, a total of 1254 manuscripts were cumulatively published. The size and label of each circle correspond to the significance of the respective keyword. Connecting lines indicate relationships between the keywords. Different colors denote distinct clusters based on their specific areas of expertise, which is presented in Fig. 5. Furthermore, based on data from the WOS database, a geographic analysis demonstrates the utilization of ANN techniques in geotechnical engineering between 2016 and 2023, as depicted in Fig. 6.

3.2 Machine learning (ML) and its application in geotechnical engineering field

ML represents a vital advancement in AI [121]. ML is achieved through iterative algorithms that learn from relevant data specific to a particular training task. This enables computers to recognize complex patterns and bring to light insights without the need for direct programming [193]. ML aims to automate analytical modeling, especially for tasks involving high-dimensional data, such as classification, regression, and clustering [121]. Different varieties of ML models contain:

Reinforcement learning: reinforcement learning involves training an agent to interact with its environment using feedback signals, aiming to develop a strategy that maximizes anticipated rewards. As indicated by [194–208], this type of ML can be classified into four methods.

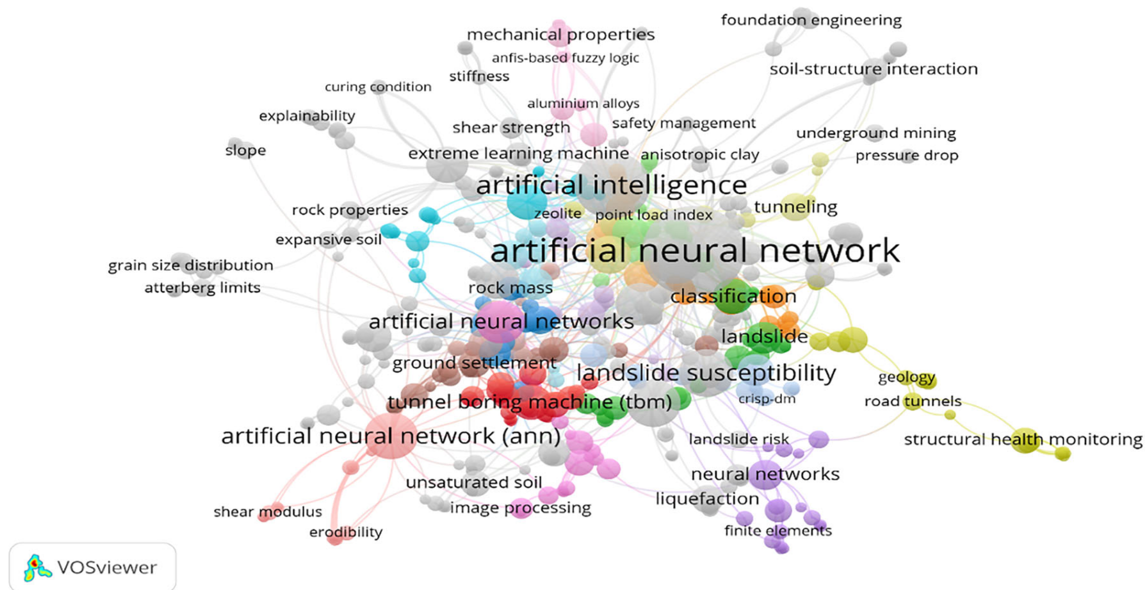

Fig. 5 Keywords related to ANN in the field of geotechnical engineering, extracted from the Scopus database

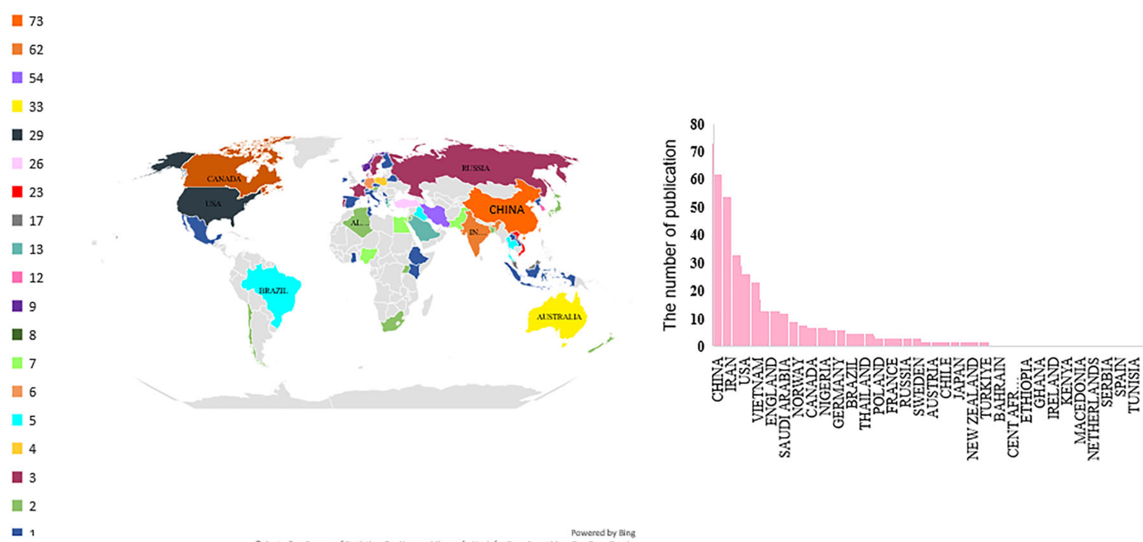

Fig. 6 Utilization of ANN techniques in the analysis of geotechnical engineering, evidenced by total publications categorized by country in the WOS database

1. Value-based methods focus on acquiring value functions (e.g., Q-values or state values) to guide action selection based on these estimates.
2. Policy-based methods directly learn policies to choose actions that lead to maximum expected rewards.
3. Actor-critic methods combine estimating value functions with policy optimization.
4. Model-based methods entail learning a model of the environment to plan and make decisions.

Unsupervised learning: unsupervised learning involves identifying patterns or structures in data without prior knowledge of the desired outcome. It is trained on data that lack labels, aiming to learn a representation that captures the inherent structure of the dataset [194–198]. This learning includes a variety of techniques, such as clustering, dimensionality reduction, density estimation, and anomaly detection [209–211]. Clustering groups similar data points based on specific features or similarities [196, 212, 213]. Dimensionality reduction methods aim to reduce the number of features while retaining important information [214–217]. Density estimation focuses on estimating the probability density function of a dataset [218–220]. Anomaly detection identifies data points that deviate significantly from expected or normal behavior

[210, 221, 222]. Some well-known and commonly used techniques in Unsupervised Learning, such as Principal Component Analysis (PCA) [223–225], K-Means Clustering [226–228], Hierarchical Clustering [229, 230], Gaussian Mixture Models (GMM) [231–233], are mentioned here.

Supervised learning: supervised learning trains an algorithm using labeled data, where each input corresponds to a known output. The algorithm learns to link input features with desired outcomes through these labeled examples. This learning process is divided into two main types: classification, which categorizes data into predefined classes, and regression, which predicts continuous numerical values. Classification yields distinct class labels, while regression deals with a range of continuous outputs [194–199, 234, 235]. Some widely recognized and commonly used techniques in supervised learning are mentioned here, including Linear Regression [236], Logistic Regression (LR) [237, 238], Bayesian Linear regression (BLR) [239, 240], Random Forest [241, 242], Support Vector Machines (SVM) [243, 244].

ML techniques, including supervised, unsupervised, and reinforcement learning, have a wide range of applications in geoengineering [245, 246]. These techniques can enhance decision-making, optimize processes, and gain geotechnical and geographical data insights [247]. Supervised learning can be applied in slope stability analysis, foundation design, and material classification [248–250], while clustering for site characterization and dimensionality reduction uses unsupervised learning [251, 252]. Additionally, reinforcement learning is applied for optimal excavation tunneling and resource management [253, 254]. The successful application of ML in geoengineering depends on the availability of high-quality data, domain expertise, and careful model selection and validation. Table 5 is dedicated to ML methodologies designed to tackle specific challenges in geotechnical engineering.

Table 4 offers a summary of recent studies exploring the utilization of ML in geotechnical engineering. These investigations contain various subjects, ranging from soil classification and spatial interpolation to slope stability and rock mass categorization. Also it contains predictions for unconfined compressive strength (UCS), evaluations of soil layering, projections for shear strength of fiber-reinforced soil (FRS), estimations of cation exchange capacity (CEC), and assessments of gully erosion susceptibility. The results of these inquiries demonstrate the effectiveness of ML algorithms in dealing with various challenges within geotechnical engineering. ML models have demonstrated notable accuracy in tasks like soil classification, spatial property variability prediction, slope stability assessment, rock mass categorization, UCS prediction, identification of soil layers, FRS shear strength prediction, CEC estimation, and gully erosion susceptibility mapping [106, 192, 269]. Furthermore, the research emphasizes the significance of factors such as the quality and representativeness of the training dataset, model complexity, and the specific application context when deploying ML algorithms in geotechnical engineering. Additionally, further validation of ML models using new databases is often necessary to evaluate their broader applicability. According to a search of the Scopus database for Elsevier journal papers, researchers published 1,401 research papers on ML in geotechnical engineering between 2016 and 2023. Figure 7 shows these data, along with keywords related to Machine learning techniques in geotechnical engineering, extracted from the most relevant articles. Moreover, as indicated by the WOS database, a geographical data analysis demonstrates the application of ML techniques in geotechnical engineering between 2016 and 2023, as shown in Fig. 8.

3.3 Deep learning (DL) and its application in geotechnical engineering field

Recently, DL has demonstrated remarkable advancements and achievements across a wide range of fields [270]. DL, a subset of ML, aims to develop algorithms that can gradually comprehend complex data representations. This is accomplished by employing neural networks consisting of interconnected layers of nodes. DL algorithms typically use extensive datasets during training, enabling them to identify complex patterns and attain highly accurate predictions [271]. DL algorithms possess the unique capability to autonomously identify features, circumventing the need for ML algorithms, which accelerates data classification processes [121]. Additionally, DL demonstrates exceptional efficiency in handling substantial volumes of information within tight timeframes. Notably, one of the most noteworthy characteristics of DL is its capacity to enhance its intelligence over time continually [270]. Table 5 provides an overview of DL methods. Other DL approaches often integrate and complement the methods outlined in Table 6 to enhance overall efficiency and effectiveness. Also, Table 7 is specifically dedicated to the application of DL techniques in the field of geotechnical engineering.

DL techniques have found applications in various aspects of geoengineering due to their ability to process and analyze complex data patterns, including geological feature detection [93, 105, 286], landslide prediction[169, 287, 288], seismic data analysis [105, 289], groundwater modeling [290], infrastructure monitoring [93, 291], soil classification[292, 293], geospatial data analysis [105, 290], mining and resource management [294, 295], environmental impact assessment [105, 296]. To implement DL in geoengineering, access to relevant datasets, machine learning and deep learning expertise, and

Table 5 Application of Machine Learning Methodologies in Geotechnical Challenges

Ref	Methodology Approach	Supervised	Unsupervised	Geotechnical classification	Advantages of the Proposed Method	Disadvantages of the Proposed Method	Result
[255]	LR + ANN + DF + DJ + SE + VE	✔	✗	Soil mechanics Soil classification	1) The study provided a data-driven approach to classify soils, which can be valuable in geotechnical and environmental applications 2) It demonstrated the importance of considering physicochemical properties, such as CF, in soil type 3) The use of ensemble methods improved the predictive performance of the models	1) The research concentrated on physicochemical characteristics, potentially ignoring other influential factors, potentially constraining its applicability in specific scenarios 2) The performance measures and outcomes specified in the study are designed for the dataset used, requiring careful consideration of their applicability to other datasets	The research showcased that the physicochemical properties of soil directly impact its plastic behavior, establishing them as dependable indicators for soil category
[256]	RBFN + MPS + BCS	✔	✗	Soil mechanics—geotechnical properties	1) Enhanced predictive accuracy in spatial interpolation by integrating spatial anisotropy via Mahalanobis distance 2) Quantification of predictive uncertainty, enabling the estimation of confidence intervals 3) Efficient performance achieved with an average number of measurement data points 4) Comparative analysis with alternative methods to evaluate strengths and weaknesses	1) Performance could be reduced with a need for measurement data 2) The MPS method depends on a high-quality training image, which might not always be accessible in real-world site investigations	The examination introduced an ensemble method based on RBFNs, which improves spatial interpolation by considering geotechnical anisotropy, providing a measure of prediction uncertainty, and outperforming traditional RBFNs in terms of accuracy and reliability
[257]	RF	✔	✗	Tunnel engineering— site investigation—geotechnical analysis	1) Improved decision-making in observational method projects 2) Determination of feature importance for identifying critical parameters influencing project outcomes 3) Real-time predictions during construction	1) The effectiveness of ML algorithms can be influenced by factors such as the dataset used and the complexity of the model	The research introduced a methodology integrating numerical analysis with machine learning algorithms to improve decision-making in observational method projects

Table 5 (continued)

Ref	Methodology Approach	Supervised	Unsupervised	Geotechnical classification	Advantages of the Proposed Method	Disadvantages of the Proposed Method	Result
[258]	RF + AdaBoost + Bagging + SE + VE + BN + DT + MLP + SVM	✔	✗	Slope failure	1) Proficiently identifies the critical causal factors contributing to slope failures 2) Implements ensemble machine learning techniques to enhance prediction accuracy 3) Introduces a novel ensemble feature selection method 4) Offers valuable insights for local-scale susceptibility zoning	1) Demands field surveys and the collection of soil samples, which can be needed resource-intensive	The examination recognized six crucial causal factors for slope failures. It revealed that ensemble RF and AB techniques surpassed other methods, achieving high AUROC (0.9722), accuracy (91.65%), and kappa statistics (0.77)
[259]	Not Mentioned	✗	✔	Slope engineering—slope classification	1) Unsupervised learning enables the identification of patterns within data 2) The research emphasizes the possible utilization of unsupervised learning techniques in the realm of slope engineering and related fields, potentially leading to new discoveries in knowledge	1) The study needs more specific details about the unsupervised learning algorithms employed, making challenges for replication or further investigation of the methodology 2) The methodology feature selection and preprocessing needs to be more detailed	The findings indicate that unsupervised learning techniques have the potential to be utilized in datasets across different domains of slope engineering, including studies on landslides and natural terrain hazards
[260]	NB + RF ANN + SVM	✔	✗	Rock mass classification	1)The research illustrated that it's possible to simplify the geotechnical field survey by using fewer variables to classify rock masses 2) ML models, specifically RF, SVM, and ANN, provided substantial predictive accuracy and stability in determining rock mass categories	1) The performance of the NB algorithm was lower when compared to RF, SVM, and ANN. Indicates that there might be more suitable models for this specific application 2) Although the study presents an encouraging foundation, further validation with new databases may be necessary to evaluate its broader applicability	The findings indicated that ML algorithms effectively predicted RMR classes. Among them, RF, SVM, and ANN exhibited superior performance, highlighting their strength in capturing predictor interactions. Although NB performed less optimally, it still holds potential as a model for forecasting rock mass classes

Table 5 (continued)

Ref	Methodology Approach	Supervised	Unsupervised	Geotechnical classification	Advantages of the Proposed Method	Disadvantages of the Proposed Method	Result
[261]	BR + LM + SCG + PCA	✔	✔	Rock mechanics—rock strength	1) Lithology-Based Distinction: This approach considers the variations in rock types, enhancing the precision of UCS predictions derived from VP measurements for specific geological formations 2) Cost-Effective and Non-Destructive: Unlike the demanding, costly, time-intensive, and damaging process of determining UCS, VP assessments are economical, accurate, non-invasive, and straightforward 3) Statistical Validation: The regression equations were statistically tested, providing confidence in their reliability for forecasting UCS from VP	Sample Preparation and Testing Constraints: Some types of rocks received limited research attention in the past due to challenges associated with preparing and testing samples, which originated from their structural anisotropy	This study presents a methodology that considers the varied lithological composition of rocks, offering a more accurate and efficient means of predicting UCS from VP for twelve distinct rock types. Each rock type displayed its distinct regression curve, facilitating precise UCS predictions based on VP measurements
[262]	Agglomerative Clustering	✗	✔	Site investigation—CPT—soil layer	1) Automation and Efficiency: The suggested algorithm offers an automated and efficient way to generate an initial layering profile, paving the way for engineering assessments 2) Overcoming Depth Limitations: The algorithm addresses a limitation of the traditional elbow method by introducing a supplemental cost function that accounts for average layer thickness	1) Dependence on Visual Inspection: The study advises a visual assessment of the algorithm-generated layering to verify its alignment with site geology and the intended application of the CPT data. Suggests that the automated method may only sometimes capture all subtleties accurately 2) Possible Grouping of Transition Layers: The algorithm may sometimes group transition layers into a single cluster, potentially affecting the accuracy of the layer identification process	The study introduced an unsupervised ML technique to autonomously detect layers within the CPT data and determine the most suitable number of layers. This algorithm employed CPT profiles sourced from the NGL database to enhance liquefaction triggering and manifestation models

Table 5 (continued)

Ref	Methodology Approach	Supervised	Unsupervised	Geotechnical classification	Advantages of the Proposed Method	Disadvantages of the Proposed Method	Result
[263]	JS + WFLSSVR	✔	✗	Soil improvement—soil reinforcement	1) Intuitive User Interface: A user-friendly interface was created to ensure easy utilization for geotechnical engineers, even those without programming knowledge 2) Simplified Analysis of Impacts: The model presented simplified the assessment of how mechanical and geometric characteristics of soils and fibers influence the shear strength of FRS 3) Innovative Feature Combinations: The model uncovered fresh combinations of features that substantially enhanced precision, making a distinctive contribution to predicting the peak friction angle of FRS	1) Reliance on Training Data: If the training data are insufficient or biased, it can result in inaccurate predictions 2) Complexity and Computational Time: Although the suggested model offers precise predictions, it may entail greater computational costs, particularly when contrasted with simpler analytical or empirical approaches	The JS-WFLSSVR model exhibited superior predictive precision compared to other models previously documented in the literature, making it a valuable tool for estimating the shear strength of FRS
[264]	SVM and ANN	✔	✗	Soil chemistry—chemical properties—CEC	1) Precision: The ANN and SVM models demonstrated the ability to predict cation exchange capacity within acceptable margins 2) Broad Relevance: The models displayed potential in forecasting soil properties, indicating their possible usefulness in agricultural research and related domains	1) Extrapolation Constraints: The ANN and SVM models demonstrated challenges in accurately projecting extreme values of CEC data beyond the range of the training set 2) Data Dependency: The effectiveness of both ANN and SVM models relies on the quality and representativeness of the training dataset. They are sensitive to the characteristics of the data used for training	The study's objective was to assess and compare the predictive capabilities of SVM and ANN techniques for estimating the CEC of soil using a range of soil characteristics as input parameters

Table 5 (continued)

Ref	Methodology Approach	Supervised	Unsupervised	Geotechnical classification	Advantages of the Proposed Method	Disadvantages of the Proposed Method	Result
[265]	BRT + BRT-bagging	✔	✗	Soil erosion–gully erosion	1) Policy Impact: The findings of this research offer crucial information for policymakers, aiding in the formulation and implementation of measures to alleviate the impacts of gully erosion 2) Sustainability Implications: This study yielded significant insights into the underlying factors influencing the frequency of gully erosion, a pivotal consideration for ensuring the sustainability of erosion-prone areas 3) Planning and Conservation: The susceptibility map generated in this study holds practical utility for informed decision-making in land and water conservation and land use planning, contributing to sustainable development efforts in the region	1) Limited to Available Data: The models' precision and reliability depend on the quality and representativeness of the available dataset. Inadequate or biased data may lead to unreliable predictions	The ensemble of BRT-bagging demonstrated remarkable accuracy in forecasting GES establishing it as a valuable tool for spatial prediction studies in this specific context

Table 5 (continued)

Ref	Methodology Approach	Supervised	Unsupervised	Geotechnical classification	Advantages of the Proposed Method	Disadvantages of the Proposed Method	Result
[266]	BLR + REG ANN + LR + BDT + RDF + DJ + VE + SE	✔	✗	Soil improvement-stabilization-strength	1) Enhanced Accuracy: Ensemble methods, including VE and SE, yielded predictions of superior accuracy in regression and multiclass classification compared to individual models and tree-based approaches 2) Resilient Predictions: By aggregating multiple learners, the ensemble methods demonstrated the ability to provide robust predictions in both regression and multiclass classification scenarios 3) Improved Error Independence: Models based on trees and meta-ensembles showed greater independence among error terms and their effectiveness in reducing random errors	Not Mentioned	The study demonstrates that ensemble methods (VE and SE) outperformed stand-alone and tree-based models in accurately predicting soil strength when enhanced with different OPC, PFA, and GGBS combinations, highlighting their versatile and robust predictive capabilities
[267]	SVM + SRM	✔	✗	Soil improvement—soil stabilization—unsaturated soil	1) SVM with SRM demonstrated high performance in predicting the geotechnical properties of the treated soil 2) It outperformed MLR in predicting Cu 3) The sensitivity analysis provided insights into the influential factors on the Cc and uniformity (Cu) predictions	1) SVMs can demand significant computational resources, particularly with extensive datasets. Its performance may be suboptimal if data preprocessing is inadequate or the selected kernel function is unsuitable	This prediction is essential for earthwork designs and construction planning, particularly in areas prone to volume changes from seasonal wetting and drying cycles. Notably, the SVM model showcased excellent performance in this regard
[268]	Multivariate Regression Methods (Linear Methods) + ANN (Nonlinear Method)	✔	✗	Soil chemistry—soil salinity	1) The neural network demonstrated higher accuracy in predicting soil salinity in comparison to regression techniques 2) Neural networks display reduced sensitivity to input errors, rendering them adaptable for modeling complex relationships	1) Implementing the neural network approach may require more computational resources than regression methods 2) Neural networks can be sensitive to the choice of hyperparameters and network architecture	The findings revealed that the neural network outperformed regression methods in accurately predicting soil salinity

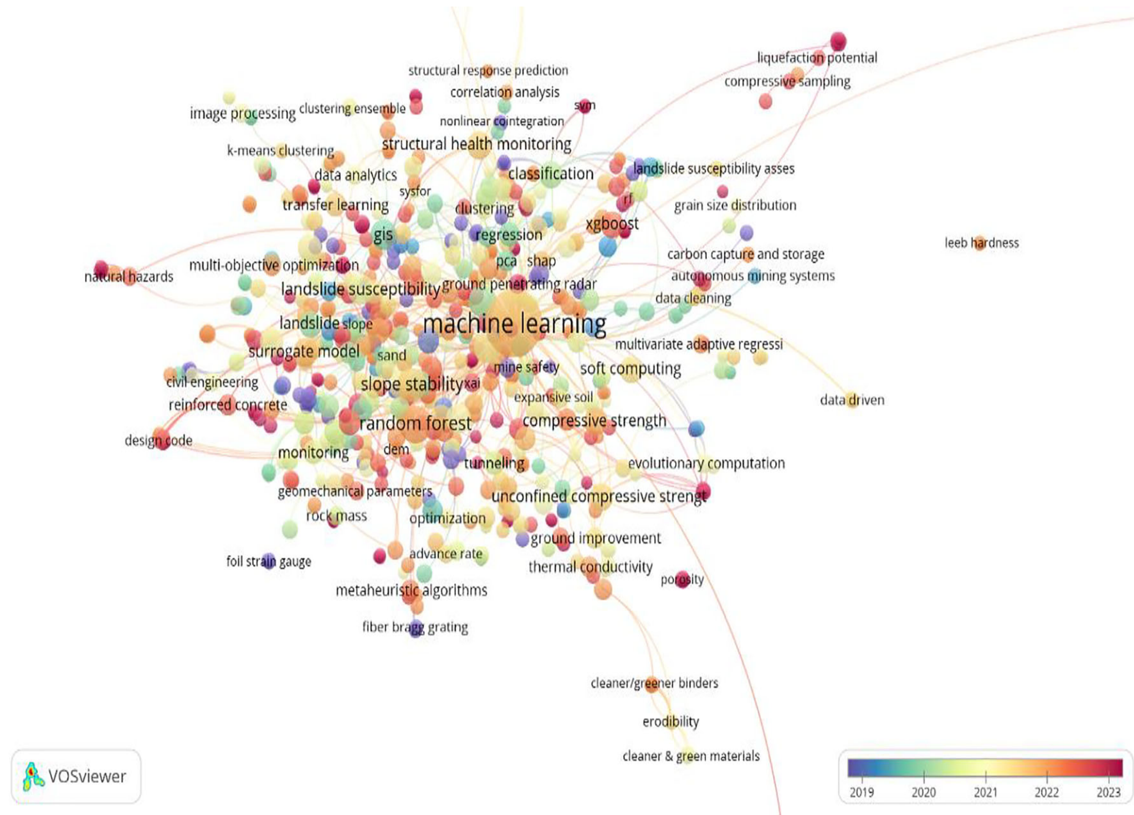

Fig. 7 ML keywords in geotechnical engineering from the Scopus database

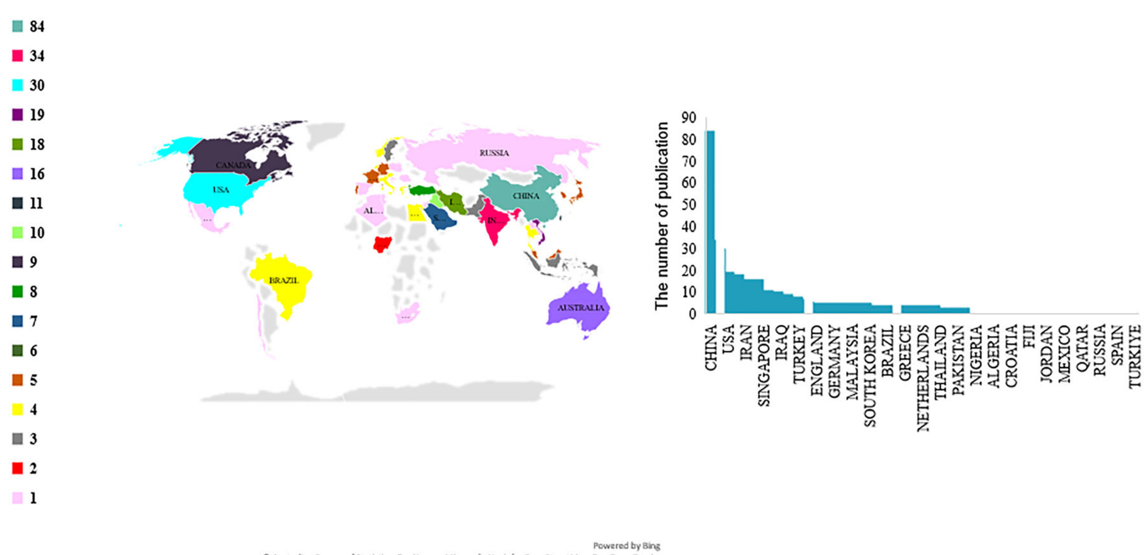

Fig. 8 Utilization of ML techniques in the analysis of geotechnical engineering, evidenced by total publications categorized by country in the WOS database

computing resources for model training will be required [297, 298].

The research conducted a keyword analysis with a specific emphasis on the utilization of Deep Learning techniques in Geotechnical Engineering. It was found that researchers published 1,040 research papers on deep learning in this field between 2016 and 2023. The data were collected from the Scopus database and visualized using VOS Viewer, as illustrated in Fig. 9; this graphical representation captures the evolving research trends

Table 6 Comprehensive Overview of DL Methods

Architecture	Description	Advantages	Disadvantages
Convolutional Neural Networks (CNNs)	CNNs are deep learning neural networks inspired by the human visual cortex to extract features from images, enabling computers to understand visual information [272]	1) Feature Extraction: Automatically achieve relevant features from images 2) Spatial Structure: Capable of understanding spatial hierarchies in visual data 3) Image Proficiency: High performance in tasks related to images	1) High Computational Requirements: Both training and inference processes can demand significant Intensive computing 2) Need Large Data: Often necessitates large quantities of labeled data for practical training 3) Lack of Interpretability: Complex CNNs can be Incomprehensible
Recurrent Neural Networks (RNNs)	In taking sequential data, an RNN analyzes each input with consideration to the preceding inputs in the sequence. This enables the RNN to influence the current input and output by utilizing information from prior inputs [273]	1) Applicable to sequence tasks like language and time-series data 2) Temporal Dependencies: Able to recognize temporal dependencies 3) Variable Length: Manage sequences with various lengths	1) Training Challenges: RNN training can be complex and time-consuming 2) Short-Term Memory: Limited memory for long-distance dependencies 3) Vanishing Gradient: may be to encounter the challenge of gradients vanishing
Deep belief network (DBN)	DBN is a prevalent form of DL neural network design often applied in unsupervised learning applications like feature acquisition, reducing dimensions, and generating models. It contains numerous layers of hidden nodes that acquire the skill to show data hierarchically [274]	1) Feature Learning: Automatically learn hierarchical features 2) Anomaly detection: Capable of discerning between typical and atypical data	1) Interpretability limitation: DBNs can create challenges in terms of understanding 2) Training Complexity: Training deep models can be challenging 3) Computational requirements: Deep models may necessitate significant computing resources
Autoencoders (AEs)	AEs are a category of neural networks for unsupervised learning, focusing on acquiring the ability to encode and decode input data [275]. Autoencoders train to reconstruct the input data, compelling the network to learn the underlying features of the dataset [276]	1) Efficient Feature Extraction: Proficiently isolates and composes vital features from the data 2) Unsupervised Learning: Capable of learning and representing data patterns without reliance on labels 3) Dimensionality Reduction: Useful for reducing high-dimensional data	1) Limited Feature Learning: Compared to specific other models, it is not strong in managing complex tasks Reliance on Reconstruction Loss: Its efficacy is contingent on the accuracy of the loss generated during the regeneration process
Deep transfer learning (DTL)	DTL is a method in ML that employs a pre-trained deep learning model to acquire proficiency in a new task. This differs from conventional ML methods, where a model is trained entirely from the foundation for each new task [277]	1) Utilizing Data Efficiently: Effective in scenarios with limited availability of labeled data, leveraging resources effectively 2) Pre-trained Models: can use pre-trained models for new tasks 3) Adaptability: Demonstrates increased flexibility in managing novel tasks	1) Domain Gap: Pre-trained models might not consistently demonstrate effective adaptability in unfamiliar domains 2) Task Incompatibility: Not all pre-trained models suit every task

spanning from 2019 to 2023. Moreover, as indicated by the WOS database, a geographical data analysis demonstrates the application of DL techniques in geotechnical engineering between 2016 and 2023, as shown in Fig. 10.

3.4 Ensemble learning (EL) its application in geotechnical engineering field

EL, a method in ML, combines the forecasts of multiple models to enhance overall performance [299, 300]. EL aims to improve predictive performance, accuracy, and generalization on various tasks [301, 302]. Ensemble methods work best when the base models are diverse, meaning they make errors on different subsets of the data or have different approaches to solving the problem [303, 304]. This diversity helps in reducing the overall error [305, 306]. Several widely recognized EL techniques include:

Bagging (Bootstrap Aggregating): This ensemble method involves training multiple models on different

Table 7 Application of Deep Learning Methodologies in Geotechnical Engineering

Ref	Algorithms	Focus	Geotechnical classification	Advantages of the Proposed Method	Disadvantages of the Proposed Method	Result
[278]	DNN, SVM, LR, GNB, MLP, BNB, DT	The research focuses on forecasting the geomechanically properties (such as uniaxial compressive strength, cohesion (c), angle of internal friction (ϕ), Young's modulus (E), and shear modulus (G)) of samples obtained from marlstone	Rock mechanics-mechanical properties	Efficiency in Time and Cost: Utilizing indirect methods, particularly those based on DL, Faster and more affordable outcomes in contrast to conventional direct approaches like on-site surveys and lab experiments	1) Data Reliance: The accuracy of the DNN model hinges on the quality and quantity of training data. Inadequate or biased data can result in less reliable predictions 2) Complex Implementation: Establishing and training a DNN demands proficiency in deep learning, which can create a challenge for people who lack the necessary expertise 3) Restricted Applicability: The model's effectiveness may be confined to marlstone samples from the South Pars region of Iran, potentially lacking robustness when applied to other rock types or various geographical locations unless further validated	The suggested model demonstrated excellent performance compared to others in terms of accuracy, precision, and error rates. It achieved high accuracy (0.95) and precision (0.97) while showing low error rates (MAE = 0.13, MSE = 0.11, and RMSE = 0.17). Furthermore, the high R-squared values (R2) (0.933 for UCS, 0.925 for E, 0.941 for G, 0.954 for c, and 0.921 for φ) illustrate a significant degree of agreement between predicted and experimental outcomes
[279]	MLP, LSTM, TCN	The research focuses on creating an innovative framework for conducting finite element (FE) analysis in the field of geotechnical engineering	Soil mechanics Constitutive behaviors of soils	1) Enhanced Applicability: The DL-based approach bypasses the need for intricate and sometimes unclear formulations found in traditional constitutive models, potentially broadening its applicability in engineering applications 2) Efficient Computation: By utilizing DL models, the necessity for stress integration at Gauss points is prevented, resulting in significant computational efficiency increases (ranging from one to two orders of magnitude) 3) Accounting for Material History: DL models take into account both the current and previous strain states as inputs, enabling the analysis to incorporate material history dependency	1) Limited to Low-to-Moderate Strain Levels: The research acknowledges limitations in regions with intense strain concentration, indicating that the proposed framework is currently most suitable for scenarios with low-to-moderate levels of strain 2) Requirement for Continued Advancement: In addressing higher strain challenges, future studies may require more accurate and robust deep learning models, such as physically informed neural networks. Additionally, they might need to incorporate advanced numerical techniques to improve the convergence of the models	The research demonstrated the effectiveness and reliability of the proposed framework by analyzing three different boundary value problems (BVPs) with varying characteristics. The LSTM model outperformed others in terms of accuracy and efficiency. Additionally, the use of DL models significantly accelerated computations compared to conventional finite element analyses

Table 7 (continued)

Ref	Algorithms	Focus	Geotechnical classification	Advantages of the Proposed Method	Disadvantages of the Proposed Method	Result
[280]	CNNs (including Xception, MobileNet_v2, Inception_ResNet_v2, Inception_v3, Densenet121, ResNet101_v2, and ResNet-101)	The research focuses on utilizing DL techniques to intelligently identify lithology through the analysis of microscopic images of rocks	Rock engineering- microscopic image-lithology identification	1) Robust and Flexible: The suggested approach demonstrated sturdy performance and the capacity to apply broadly, rendering it applicable for swift lithology identification by both geologists and engineers 2) Extracting Characteristics: CNNs proficiently extract features, particularly in situations where conventional image processing techniques might face difficulties	1) Possibility of Incorrect Identification: There are instances where rocks sharing similar mineral compositions could be mistakenly identified, possibly resulting in inaccurate outcomes 2) Data Dependency: The model's precision and efficiency could be influenced by the quality and variety of the training data 3) increase dataset: The dataset might be imperative to enhance performance across a broader range of rock varieties	The Xception-based model achieved remarkable accuracy at 98.65% in the testing dataset, outperforming six other models. It also demonstrated efficient identification with a speed of 50.76 frames per second, emphasizing its superiority over other CNNs in the research
[281]	physics-informed DL model	The study focuses on illustrating the capacity of physics-informed DL models in the field of geomechanics, particularly in addressing 1D consolidation issues	Soil mechanics—consolidation	1) Utilizing Physics-Based Constraint: By incorporating the governing partial differential equation (PDE) as a constraint, the model ensures accurate predictions, resulting in more reliable and meaningful outcomes 2) Efficient Predictions: The model showcases the capability for accelerated, real-time numerical forecasts, offering significant advantages in time-sensitive applications like digital twins 3) Estimation of Parameters: This method can anticipate material parameters, assisting in the reproducibility of numerical models and the optimization of constituent material and model attributes	Simplicity of Application: The research emphasizes a relatively simple 1D consolidation issue. Investigating the applicability of this approach to more complicated geomechanical problems involving numerous equations and parameters might be necessary to determine its effectiveness	The suggested DL model demonstrates impressive accuracy in predicting both forward and inverse problems related to 1D consolidation. It effectively forecasts pore pressure and the consolidation coefficient, emphasizing the promising potential of this approach
[282]	RNN, CNN, LSTM, Bidirectional LSTM (Bi-LSTM) Model, GoogLeNet (a type of CNN) + ResNet-18 (a type of CNN), Continuous Wavelet Transformation (CWT)	This research focuses on identifying the ground situations at the working face of a Tunnel Boring Machine (TBM) using vibration data	Ground identification	1) A real-time analysis framework: A real-time analysis enables quick identification of ground types 2) Improved preprocessing: Raw data enhance the accuracy of the prediction model 3) CNN models: CNNs significantly outperform RNN models, attaining a notably high level of accuracy	1) Requires a substantial dataset: Obtaining a large volume of accurately labeled data for training can be a time-intensive process 2) Specification selection: Installation of accelerometers must be carefully evaluated considering geological conditions and TBM characteristics	LSTM and Bi-LSTM models attained an accuracy of about 80% using preprocessed data. In contrast, CNN models (GoogLeNet and ResNet-18) achieved notably higher accuracies, surpassing 96%, with ResNet-18 demonstrating the highest accuracy at 98.28%

Table 7 (continued)

Ref	Algorithms	Focus	Geotechnical classification	Advantages of the Proposed Method	Disadvantages of the Proposed Method	Result
[283]	CNNGeoNet	This study concentrates on utilizing image-driven DL techniques, CNNs, for the stability analysis of geosystems, with a specific emphasis on retaining walls	Stability analysis	1) High Accuracy: high accuracy for predicting the stability of retaining walls 2) Efficient Classification: The trained CNN exhibited exceptional classification proficiency 3) Potential for Big Data Solution: Presents a promising big data solution applicable to geotechnical engineering and various fields in civil engineering	1) Data Dependency: The CNN's performance dramatically depends on the scale and caliber of the dataset employed during training 2) Computational Resources: The availability of computational strength and resources can influence the utilization of DL in stability assessment	The suggested CNNGeoNet achieved an impressive success rate exceeding 97% in the classification of retaining walls. External validations corroborated the accuracy, precision, and recall metrics acquired during both the training and validation phases
[284]	Physics-Informed Neural Network (PINN)	This research focuses on forecasting ground deformations by tunneling-induced activities via a hybrid DL model	Ground (soil) deformation	1) Generalizability: The PINN model demonstrates a robust ability to generalize and effectively replicate ground deformation patterns even with limited training data 2) Resilience: The PINN model showcases outstanding robustness and minimal reliance on training data, making it suited for geotechnical applications 3) Efficient Prediction: The suggested model offers precise forecasts of ground deformation patterns while maintaining high computational efficiency, thereby diminishing the necessity for extensive training data	Reduction in Assumptions: The underlying physics framework relies on the plane strain assumption, which might only partially include the complexities of 3D dynamic excavation procedures and the spatial variations in geotechnical characteristics	The PINN model excels beyond data-driven models by accurately representing the underlying physical parameters, enabling it to create dependable surrogate models for forecasting ground deformation
[285]	Schema GAN	This research focuses on the model that creates subsoil representations using Cone Penetration Test (CPT) data	Site investigation-CPT	1) High-Quality Schematizations: Schema GAN generates high-quality subsoil schematizations, achieving realism and accuracy even with input data comprising less than 1% of the original dataset 2) Better performance: Compared to conventional interpolation techniques, Schema GAN demonstrates superior performance in terms of precision, layer boundaries, and anisotropy within layers 3) Robustness to CPT Location: SchemaGAN shows greater resilience to variations in the location of CPT data along the cross-section, compared to alternative methods	1) Data Preprocessing: Certain applications may find extensive data preprocessing to be a limiting factor 2) Irregular Topography: Schema GAN may encounter difficulties in handling subsoil structures with irregular or diverse topography 3) Complex Layer Boundaries: Accurately delineating layer boundaries can be a challenge in complex subsoil structures	Schema GAN outperforms conventional interpolation techniques in generating subsoil schematizations

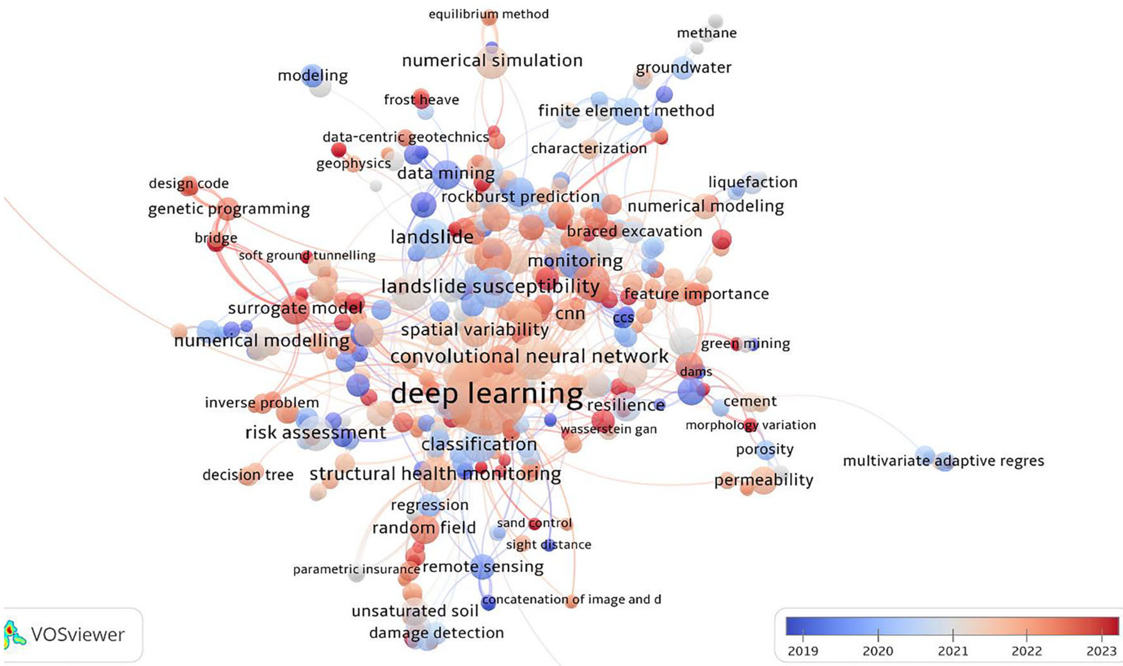

Fig. 9 DL keywords in geotechnical engineering from the Scopus database

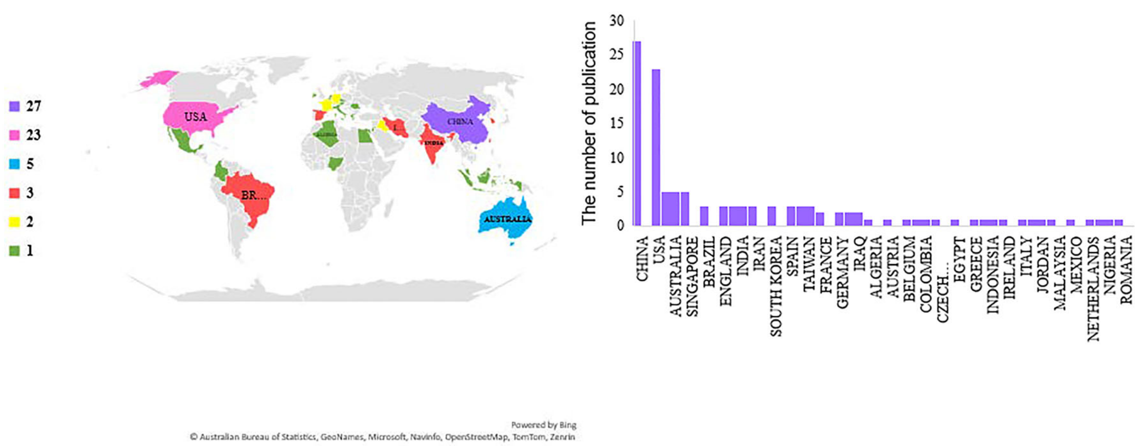

Fig. 10 Utilization of DL techniques in the analysis of geotechnical engineering, evidenced by total publications categorized by country in the WOS database

subsets of the data, and their predictions are aggregated [307–309]. Random Forest [310, 311] and Bagged Decision Trees [312–314] are the well-known methods in this category.

Boosting: Boosting enhances predictive performance by training weak models sequentially. Each model corrects the mistakes made by its predecessor, resulting in a strong learner within the ensemble [315, 316]. AdaBoost (Adaptive Boosting) [317–319], Gradient Boosting Machines (GBM) [320–322], XGBoost (Extreme Gradient Boosting) [323–325], LightGBM (Light Gradient Boosting Machine) [326, 327], and CatBoost (Categorical Boosting) [328, 329] are widely recognized techniques within this classification.

Stacking Ensembles (SE): In this approach, a meta-model is trained to learn how to best combine predictions from the base models [330, 331]. Stacking Classifier [332–334] and Stacking Regressor [335, 336] are recognized techniques within the SE category.

Voting Ensembles (VE): Models in this ensemble provide predictions, and a majority vote determines the final output [337, 338]. Hard Voting [339–341] and Soft Voting [342–344] are established methods within the VE classification.

In geotechnical engineering, EL technique is frequently employed to heighten the precision of soil and rock behavior predictions [345]. In geotechnical engineering,

Table 8 Using of Ensemble Learning Technique in Geotechnical Engineering

Ref	Algorithms	Focus	Geotechnical Classification	Advantages of the Proposed Method	Disadvantages of the Proposed Method	Result
[358]	XGBoost + RFR + DTR + MLPR + MARS	The research focuses on machine learning techniques, particularly ensemble learning methods, to forecast lateral wall deflection (δhmax) in braced excavations involving soft clay soils	Deep excavation-lateral diaphragm wall deformation	1) Stabilization: The proposed method exhibits a notable stability feature in its predictions 2) Automation: ML models offer a rapid and efficient approach to estimating wall deflection, alleviating the requirement for time-consuming finite element analyses	1) Data Dependency: The effectiveness of machine learning models is contingent on the abundance and representativeness of the available data. Inadequate or biased data can lead to inaccurate predictions 2) Interpretability: Ensemble learning methods can be complex and challenging, making understanding the reasons behind predictions difficult 3) Limited Generalization: The study covers specific scenarios and soil properties. The extent to which the models can be applied to different conditions and contexts may be constrained	XGBoost and RFR demonstrated excellent performance in predicting δhmax compared to traditional methods, emphasizing the importance of data quality and feature selection in influencing predictive accuracy, potentially over the impact of the algorithm choice
[360]	CNNs	The research addresses the difficulties of the spatial variability of soil properties, which can lead to uncertainties in geotechnical structures	Slope stability	1) Improved Accuracy: The hybrid strategy enhances the accuracy of failure probability forecasts, particularly for scenarios with lower probability levels 2) Adaptive Training: The adaptive training strategy improves the performance of CNNs in modeling the failure probability distribution sequence 3) Effective Modeling: MaxEnt-FM models the distribution sequence based on restricted sample FoS values, contributing to accurate predictions	Not Mentioned	The hybrid strategy proposed (CNNs-MaxEnt-FM) demonstrates a remarkable capability in accurately predicting low-level failure probabilities for slope stability. Moreover, it substantially reduces computational costs compared to the alternative schemes considered

Table 8 (continued)

Ref	Algorithms	Focus	Geotechnical Classification	Advantages of the Proposed Method	Disadvantages of the Proposed Method	Result
[279]	MLP + LSTM + TCN	The study uses the complexities of the complex mechanical behaviors of soils and recognizes the constraints of conventional constitutive models in geotechnical engineering	Geotechnical reliability analysis	1) Delete of Constitutive Theories: The DL-based framework removes the need for traditional constitutive theories, providing a more flexible and less constraining approach 2) Computational Efficiency: The framework significantly enhances computational speed by bypassing stress integration at Gauss points, reducing analysis time by one to two orders of magnitude 3) Material History Dependency: The framework considers present and prior strain states as inputs, effectively addressing material history dependency	1) Suitability for Small-to-Medium Strain Levels: The research emphasizes that the framework is best suited for small-to-medium strain issues, with potential challenges in handling larger strain levels and instances of pronounced strain localization 2) Region-Specific Differences: The study notes that noticeable differences are observed in regions with strong strain localization, indicating that specific complex scenarios may present challenges for the proposed framework	The research introduces an innovative Finite Element (FE) framework incorporating a DL model to characterize soil constitutive behaviors. This approach avoids traditional approaches and demonstrates computational efficiency in addressing geotechnical issues
[361]	ANN + DL + SVM + LSSVM	The objective of this study is to utilize Deep Learning (DL) as a classification technique for predicting soil liquefaction susceptibility	Soil mechanics—soil liquefaction	1) Complex Relationship Modeling: DL can model complex relationships between seismic and soil parameters without requiring predefined mathematical relationships, making it suitable for real-world data 2) Adaptiveness: DL is an adaptive computational model that learns from data and past experiences; adaptability ensures that its predictive capabilities enhance over time 3) Data-Driven: DL models rely on the information within the data itself; this means they can determine patterns and correlations that might not be easily explained through traditional mathematical formulations	Not Mentioned	The study employed DL techniques to forecast soil liquefaction susceptibility. In testing, Model I demonstrated superior performance compared to Model II

Table 8 (continued)

Ref	Algorithms	Focus	Geotechnical Classification	Advantages of the Proposed Method	Disadvantages of the Proposed Method	Result
[362]	SAEs + ANN + RBF	This research aims to develop an objective and precise method for classifying the quality of rock masses. Additionally, decreases reliance on human expertise and minimizes subjectivity in the classification process	Rock mechanics- rock mass classification	1) Objectivity: The method eliminates the need for experts to assign parameter scores and weights, relying solely on statistical correlation 2) High Accuracy: The SAE-based approach demonstrated an impressive prediction accuracy of nearly 100%, Beyond the performance of other conventional models 3) Generalizability: The method's successful application to three actual engineering slopes produced promising results and suggests its potential for broader use in geotechnical and rock engineering practices 4) Automation: The DL approach can automate the rock mass quality classification, offering time and effort compared to manual assessments	1) Data Dependency: Deep learning models like SAEs rely on extensive datasets for practical training. The model's performance depends on the availability and quality of the training data 2) Computational Resources: DL models can be computationally intensive, demanding robust hardware for training and inference processes 3) Model Complexity: While DL can offer high accuracy, it tends to lead to more complex models, which may be challenging to maintain and update	The DL technique utilizing SAEs displayed an outstanding prediction accuracy of nearly 100% for rock mass quality classification. Compared to alternative models like ANN and RBF, the SAEs outperform, achieving category accuracies of 97.5% for ANN and 98.7% for RBF
[363]	FC-SAE + SVM + BPNN	The aim of this study was to develop a deep learning-based algorithm, (FC-SAE) for the prediction of landslide susceptibility prediction (LSP)	Landslide susceptibility	1) Feature Extraction: The FC-SAE algorithm extracts essential nonlinear features from environmental variables, thereby improving the model's capacity to forecast landslides 2) Decreased Computational Requirements: The FC-SAE is reported to reduce computational demands, making it a more efficient choice for landslide susceptibility evaluations 3) Overcoming Limitations: The FC-SAE is proposed to surpass the constraints of conventional ML methods, especially in scenarios involving uncorrelated or nonlinearly correlated environmental factors	1) Data Dependency: As with many deep learning approaches, the effectiveness of FC-SAE relies on having a substantial amount of high-quality training data 2) Model Complexity: FC-SAE, like other deep learning models, can be complex and less interpretable, making it challenging to discern why specific predictions are made 3) Training and Tuning: Achieving optimal performance with FC-SAE may necessitate expertise in training and tuning hyperparameters, which can be both time-consuming and computationally demanding	The FC-SAE model demonstrated higher prediction rates and total accuracies than SVM-only and BPNN models

Table 8 (continued)

Ref	Algorithms	Focus	Geotechnical Classification	Advantages of the Proposed Method	Disadvantages of the Proposed Method	Result
[364]	CNNs + PLS + Cubist regression tr	The study utilizes CNNs to predict soil properties using unprocessed soil spectra data. This application is particularly relevant in the context of extensive regional datasets	Soil mechanics—soil properties	1) High Accuracy: The CNN model showed significantly higher performance levels 2) Simplicity of Data Preprocessing: The approach used the data preprocessing step, representing the raw spectral data as a spectrogram; this approach, though not commonly utilized in soil spectroscopy, proved effective 3) Multi-tasking Capability: The CNN was trained to predict six soil properties concurrently using a single spectrum, simplifying the process and reducing computing time. It also holds the potential to improve predictions compared to single property prediction	1) Data Size Dependency: The multi-task CNN exhibited reduced effectiveness on smaller datasets, performing worse results than the traditional Cubist model	This approach outperformed traditional methods, particularly in multi-tasking scenarios, marking a significant stride forward in soil spectroscopy

stacking is a frequently used EL method [346, 347]. This involves training multiple ML models on the same dataset and combining their predictions to generate a conclusive forecast, which can be executed through techniques like weighted averaging or voting [348]. Another common technique utilized in geotechnical engineering is Bagging [349–351]. Multiple ML approaches are trained on distinct subsets of the dataset, and their predictions are aggregated to form a final prediction. This helps mitigate the overfitting of the models to the training data [352–354].

It is important to note that the choice of EL method and the specific application will depend on the nature of the geoengineering problem, the available data, and the goals of the analysis [93, 286, 355, 356]. EL can significantly enhance the predictive capabilities and robustness of models in geoengineering, ultimately leading to safer and more effective engineering solutions [357–359]. EL is a developing field ready to have a revolutionary impact on geotechnical engineering. Table 8 provides a collection of recent studies that have successfully utilized EL to address a range of challenges in the field of geotechnical engineering. These include forecasting soil liquefaction susceptibility, categorizing rock mass quality, approximating lateral wall deflection in braced excavations, projecting soil properties through raw soil spectra data, and anticipating landslide susceptibility. These efforts emphasize the potential of EL in increasing the accuracy, efficiency, and reliability of geotechnical analyses and designs [357, 363].

The data, sourced from the Scopus database, were subsequently visualized using VOS Viewer. Over the period from 2016 to 2023, researchers published 609 research papers on ensemble learning in geotechnical engineering. The size and label of each circle in the visualization indicate the significance of the respective keyword, while connecting lines signify relationships between them. Figure 11 presents these data along with keywords associated with Ensemble Learning (EL) approaches in geotechnical engineering, extracted from the most pertinent articles. Furthermore, according to the WOS database, the application of EL techniques in geotechnical engineering is demonstrated through geographical data analysis, as depicted in Fig. 12, which visually depicts the research pattern observed from 2020 to 2023.

To gain insight into the performance of various EL-based models in the geotechnical field, Kardani et al. [293] examined the effectiveness of different EL techniques in predicting the resilient modulus of subgrade soils. They found that the bagging ensemble model outperformed other models tested, including the voting ensemble, voting ensemble with random forest, and stacking ensemble. Their conclusion was that the bagging ensemble outperformed other methods, making it suitable for estimating the resilient modulus with superior performance and an

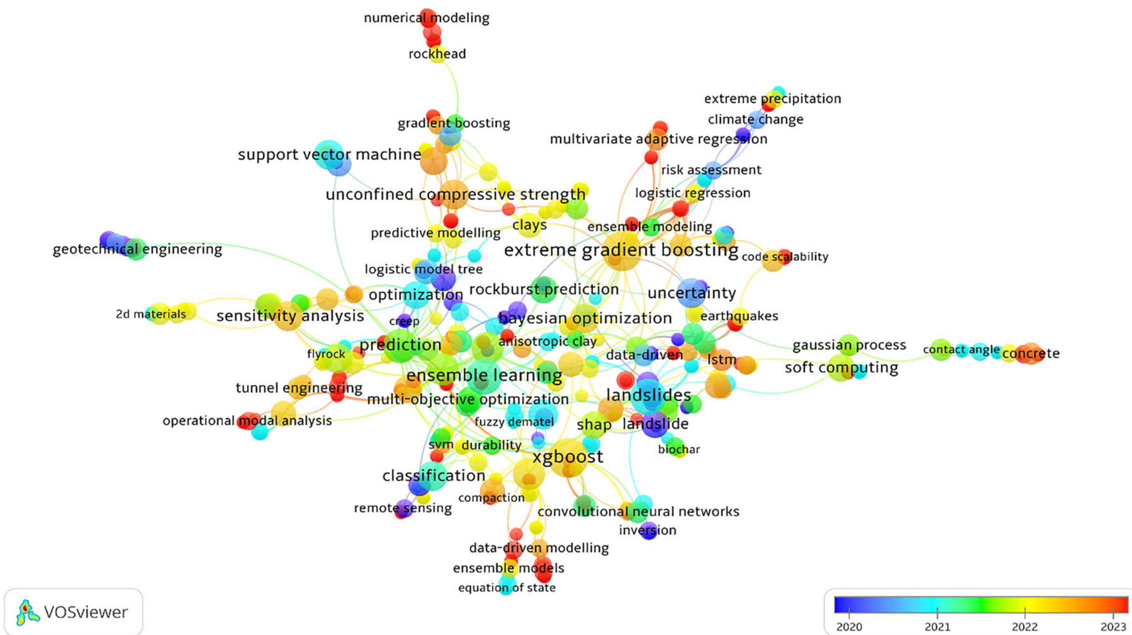

Fig. 11 Keywords related to EL in the field of geotechnical engineering, extracted from the Scopus database

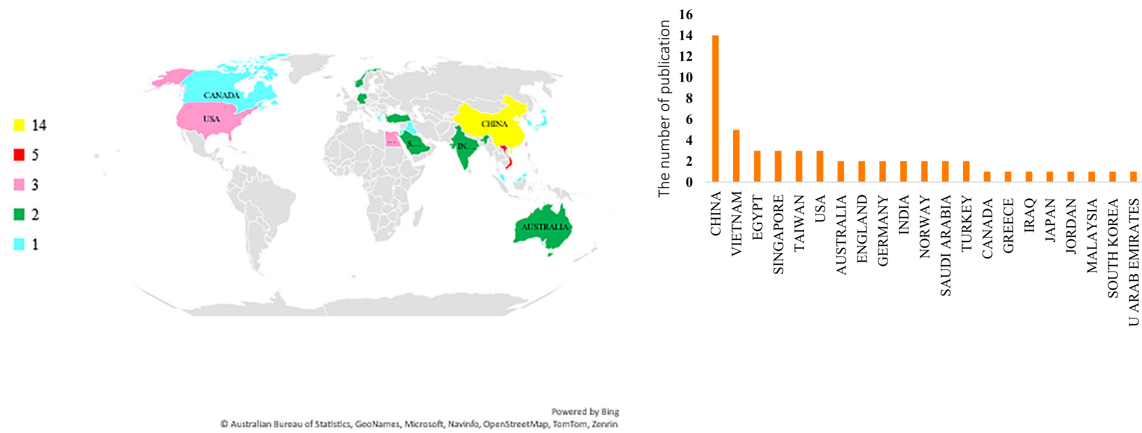

Fig. 12 Utilization of DL techniques in the analysis of geotechnical engineering, evidenced by total publications categorized by country in the WOS database

acceptable degree of accuracy. This model not only demonstrated higher prediction accuracy and generalization ability, but also exhibited several advantages such as stability, reduced noise, and ease of use. On the other hand, learning the art of ensemble modeling can be challenging, and making incorrect selections may lead to reduced prediction precision. Additionally, ensemble modeling can be costly in terms of both time and space. However, additional research using various datasets should be conducted to predict different geotechnical parameters, ensuring the performance of the bagging ensemble methods and other EL-based methods. Therefore, it is strongly recommended to utilize EL-based methods in the geotechnical field for predicting mechanical, physical, and chemical properties of soils. Further research is necessary to make reliable decisions about their performance in the geotechnical area.

4 Discussions and challenges linked with AI in geotechnical engineering

ANN models are adaptable and capable of capturing complex patterns in data. However, these models require precise adjustment of hyperparameters to achieve peak performance [116]. The performance of ANN depends on factors such as architecture, data quality, and data quantity [124, 365, 366]. Therefore, ANN is able to be the best choice for small datasets or when interpretability is crucial.

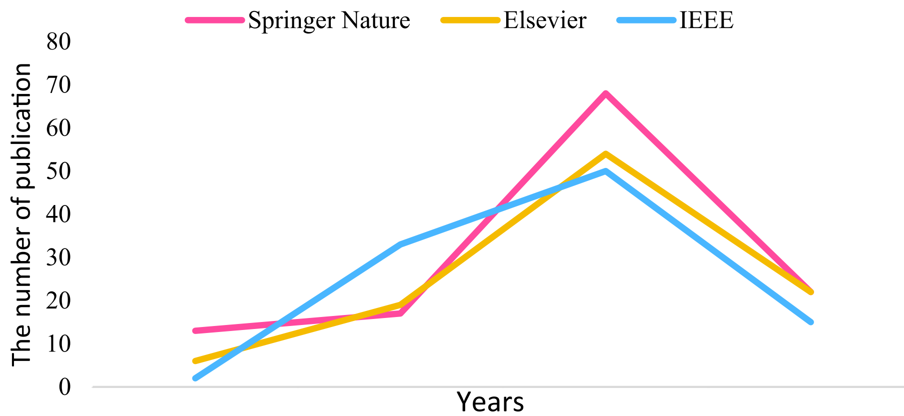

Fig. 13 Comparative analysis of esteemed journals (Springer, Elsevier, and IEEE) in the domains of ANN, ML, DL, and EL in geoengineering, 2019–2023, using the WOS database

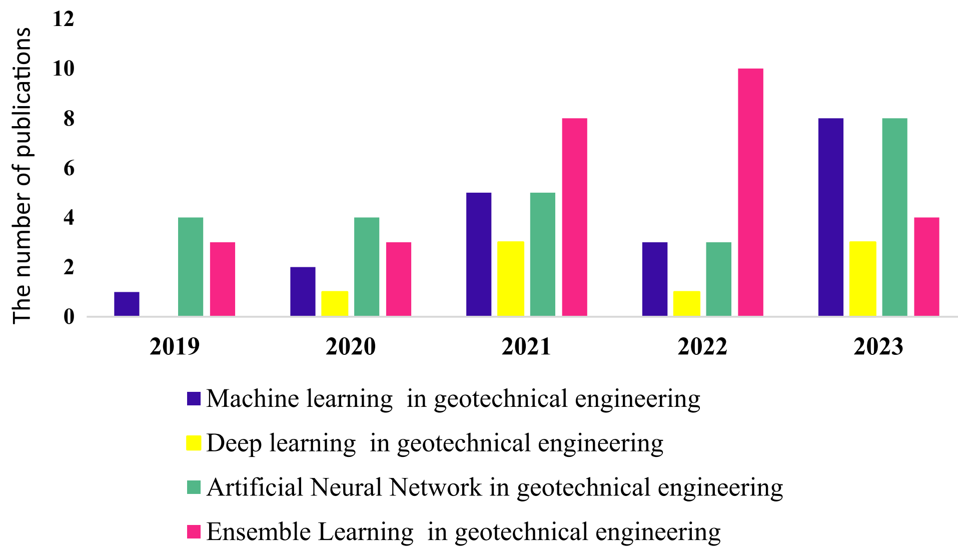

Fig. 14 Comparison of various ANN, ML, DL, and EL methods used in geotechnical engineering based on the total number of publications from 2019 to 2023, using the WOS database

Various techniques are included in ML models, such as supervised learning, unsupervised learning, or reinforcement learning, which are well suited for different tasks. The performance of ML models varies according to the algorithm and the data being utilized. In comparison to DL models, ML models are frequently found to be more interpretable [367, 368]. They are considered a favorable option when there are limited data or the need for transparent models [117].

DL models, such as CNNs and RNNs, manage extensive, high-dimensional datasets proficiently. They can automatically acquire hierarchical features [369, 370]. DL demands significant computational power, sizable datasets, and precise parameter optimization. Additionally, DL models may not always offer interpretability, which can present limitations in certain use cases [118].

EL combines multiple models to enhance predictive performance, often surpassing the performance of individual models. It achieves this by reducing overfitting and increasing robustness, making it suitable for diverse

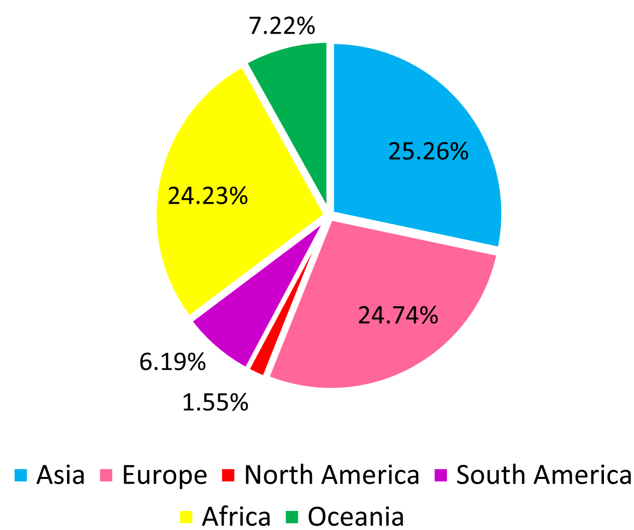

Fig. 15 Continental comparison of ANN, ML, DL, and EL in geotechnical engineering (2016–2023) using WOS database

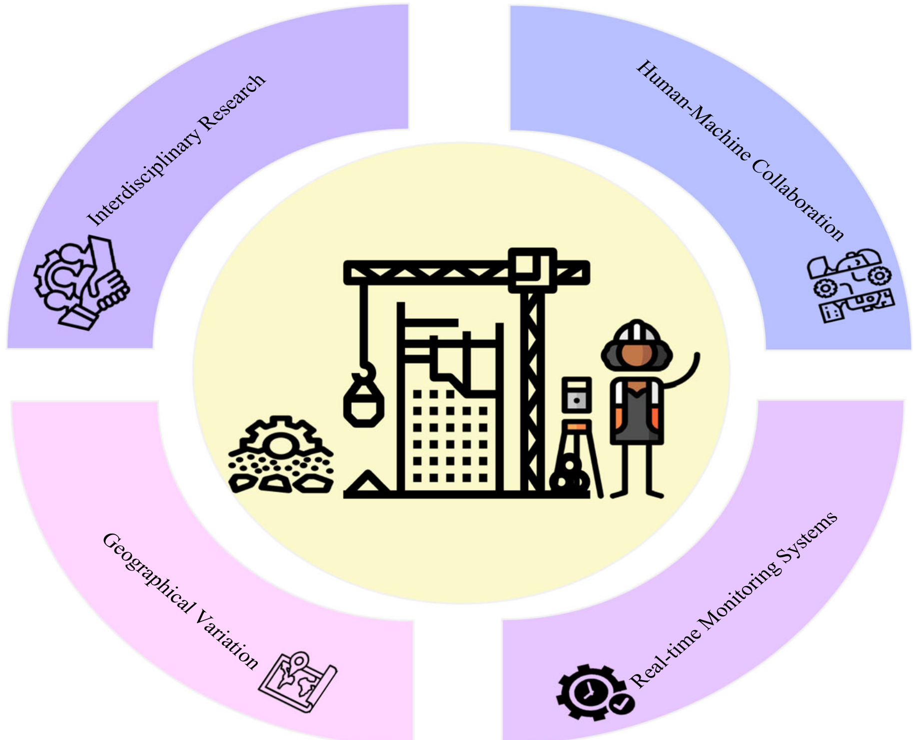

Fig. 16 Visual overview of key future research directions in the application of AI within the realm of geotechnical engineering

datasets and applications [119]. Furthermore, EL demonstrates a reduced susceptibility to noise and outliers [371].

Assessing ANN, ML, DL, and EL for geoengineering in terms of accuracy and performance can be a complex task, given that the efficacy of each method relies on diverse variables, such as the particular problem, dataset characteristics, and model setup. These approaches rely on geoengineering problems, the data, computational resources, and interpretability needs. Both ML and ANN demonstrate a moderate level of complexity and are mainly applied in the field of geotechnics. Notably, ML has attracted substantial attention from researchers due to its high interpretability and optimal performance, even with small data. This interest is substantiated by data from WOS covering the period from 2019 to 2023, which reveals that a significant number of articles published in Springer Nature, Elsevier, and IEEE journals within the geotechnical domain underscore the prevalent preference for employing ML among researchers in this field as shown in Fig. 13.

Figure 13 illustrates the number of research papers published in reputable journals, such as those from Springer, Elsevier, and IEEE, focusing on the areas of ANN, ML, DL, and in the field of Geotechnical Engineering. These data have been sourced from WOS.

Based on data from the WOS database, ANN is frequently employed in geotechnical engineering, even though ML, DL, and EL methods have demonstrated substantial potential as illustrated in Fig. 14. This preference for using ANN in geotechnical engineering may be attributed to the common requirement for real-world laboratory data frequently encountered by civil and geotechnical engineers or the potential limitation in expertise for effectively employing ML, DL, and EL methods in data-driven prediction. However, EL techniques consistently outperform the other three methods in the context of predicting geotechnical behaviors.

According to the data obtained from the WOS database, Fig. 14 provides an overview of the utilization of ANN, ML, DL, and EL approaches in geotechnical engineering from 2019 to 2023. The data clearly show that ANN has maintained its status as a consistently preferred technique within this field. Additionally, it is noteworthy that ML has exhibited a steady and upward trend over the years. In 2022 and 2023, researchers demonstrated a nearly equal preference for both ANN and ML techniques within the field of geotechnical engineering.

As depicted in Fig. 14, it is evident that the EL methods have been consistently popular over the years. Notably, the utilization of EL in the field of geotechnical engineering experienced a substantial increase from 2021 to 2022, reaching its peak adoption rate during this period. DL methods have not been widely adopted in recent years, but they started gaining recognition in geotechnical engineering in 2020. However, their popularity among geotechnical engineers remains limited due to the substantial amount of data required for accurate forecasting using this learning approach.

A widespread trend toward the utilization of artificial intelligence techniques, including ANN, ML, DL, and EL, in the field of geotechnical engineering is observed globally. This analysis, spanning from 2016 to 2023, involves the classification of data using WOS enabling thorough examination of transformations on a continental scale (refer to Fig. 15). This comparison reveals that this subject matter is actively embraced across all continents.

5 Future research directions and opportunities linked with AI application in geotechnical engineering

Future research in the field of geotechnical engineering and artificial intelligence (AI) should prioritize interdisciplinary collaboration, bringing together geotechnical engineering expertise and AI proficiency. This synergy has the potential to yield innovative solutions and provide a deeper understanding of how AI can effectively address the multifaceted challenges within geotechnical engineering. Furthermore, researchers should investigate geographical variations in the utilization of AI techniques in geotechnical engineering, examining how these methods are applied differently in various regions and identifying the factors influencing these variations. Additionally, the integration of AI for real-time monitoring and decision-making during geotechnical construction and operations should be explored, focusing on the development of adaptive AI-driven systems that can enhance safety and operational efficiency. Finally, researchers should delve into the concept of human–machine collaboration, examining how AI can assist geotechnical practitioners in decision-making, risk assessment, and project design. These research directions, aligned with the standards of scholarly articles, aim to foster innovation and provide practical solutions for the geotechnical engineering community. Figure 16 offers a visual depiction of the critical future research direction in the application of AI within the realm of geotechnical engineering.

From a geotechnical engineering perspective, there are numerous topics that can still be studied and addressed in future research. One potential area of research is the application of various AI methods to predict the dynamic response of different soils, contingent on the availability of adequate datasets. In addition, a simple review of Tables 4, 5, 7, and 8 and available papers in the field of geotechnical engineering confirms that soil improvement, as a hot topic in general, has received less attention from the AI approach. It is well known that soil properties, including soil gradation, consistency, compaction parameters, consolidation, dispersivity, collapsibility, swelling potential, durability, strength, elasticity, stress–strain curves, peck strain energy, resilient modulus, dynamic response, erodibility, chemical compositions, hydraulic conductivity, electrical conductivity, and liquefaction potential, can be altered through stabilization with traditional materials like lime and cement, or through the use of waste by-products such as lignosulfonate, travertine waste, red mud, sewage sludge, water treatment sludge, fly ash, various types of slags, as well as soil reinforcement using different materials like fibers and geosynthetic materials, or alternative soil improvement techniques such as electroosmosis [46, 372–385]. However, it is evident that AI-based prediction of soil parameters after stabilization or reinforcement with various techniques and materials deserves more attention, especially considering the substantial number of experimental papers in this field and the availability of sufficient datasets. Therefore, future research studies can focus on the prediction of stabilized and reinforced soil parameters.

6 Conclusions

ANN, ML, DL, and EL are pivotal approaches for extracting valuable insights and making autonomous predictions in various fields, including geotechnology. This study aimed to comprehensively assess the applications of these techniques in geoengineering, filling a critical gap in the existing literature.

Evaluation of a vast dataset extracted from the Web of Science and Scopus databases revealed significant insights. ANN remains a widely used technique in geotechnical engineering, often due to the necessity for real-world laboratory data frequently encountered by civil and geotechnical engineers. Additionally, the expertise gap in effectively applying ML, DL, and EL methods for data-driven predictions may influence the preference for ANN. However, when it comes to predicting geotechnical behaviors, EL techniques consistently outperform the other three methods, showcasing their effectiveness in this domain.

Each of these techniques possesses its unique strengths and limitations. ANN models are adaptable and excel at capturing complex data patterns, but they require meticulous hyperparameter tuning and are suitable for scenarios with limited data or where interpretability is crucial. ML models encompass various techniques suitable for diverse tasks, offering interpretable solutions and being favored when data are limited. DL models handle high-dimensional data effectively but demand substantial computational resources and careful parameter optimization. Conversely, EL combines multiple models to enhance predictive performance, exhibiting robustness and reduced sensitivity to noise and outliers. The integration of ANN, ML, DL, and EL techniques has significantly contributed to advancing the field of geotechnology. Researchers and practitioners in this domain should continue to explore and harness the potential of these methodologies to address the evolving challenges in geotechnical engineering effectively.

Author contributions Elaheh Yaghoubi involved in supervision, conceptualization, methodology, writing—reviewing and editing. Elnaz Yaghoubi took part in software, data curation, writing—original draft. Ahmed Khamees involved in visualization, investigation. Amir Hossein Vakili took part in supervision, conceptualization, methodology, writing—reviewing and editing.

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Data availability The datasets generated during and analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare no conflict of interest.

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